FRACTIONAL INTEGRATION

AND POLITICAL

MODELING

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This dissertation investigates the consequences of fractional dynamics for political modeling. Using Monte Carlo analyses, Chapters II and III investigate the threats to statistical inference posed by including fractionally integrated variables in bivariate and multivariate regressions. Fractional differencing is the most appropriate tool to guard against spurious regressions and other threats to inference. Using fractional differencing, multivariate models of British politics are developed in Chapter IV to compare competing theories regarding which subjective measure of economic evaluations best predicts support levels for the governing party; egocentric measures outperform sociotropic measures. The concept of fractional cointegration is discussed and the value of fractionally integrated error correction mechanisms are both discussed and demonstrated in models of Conservative party support. In Chapter V models of presidential approval in the United States are reconfigured in light of the possibilities of fractionally integrated variables. In both the British and American case accounting for the fractional character of all variables allows the development of more accurate multivariate models.

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CHAPTER I

INTRODUCTION

1.1 Introduction

One of the most important reasons why the integration of statistical methods into the study of politics has failed to bring about the behavioralists' anticipated 'golden age' is the lack of consensus among researchers regarding how to employ their new statistical tools. This problem is compounded in areas where the methodology itself is either flawed or overly restrictive. With these problems, ideas and models that may make sense theoretically leave themselves open to criticism on the basis of methodology. Ultimately, these models may be discarded as the specification process begins anew. One escape from this dilemma is the development of methodological approaches capable of minimizing the subjectivity employed by researchers. Such an escape seems possible for analysts of time-series data as a greater understanding of the need and value of using the fractional differencing parameter, *d*, could lead to a greater consensus regarding model specification.

Until recently, researchers using time-series data have been confined to the "knife-edged" decision of whether to treat their data as deriving from an I=0 (stationary) or I=1 (unit-root) process. On the basis of this choice, researchers would then either difference their data (if they believed it to be derived from a unit-root process) or leave it in level form (if they believed it to be stationary). The importance of this decision is highlighted when the theoretical and empirical consequences are noted. Theoretically, classifying a variable as a stationary process implies that, *ceteris paribus*, its value at previous periods is forgotten at a consistent rate as it tends toward some long-term mean. However, treating a variable as a unit-root implies the belief that it has perfect memory - that is, its value at each period is its value at the previous period plus any shock incurred since the previous period.

From an empirical standpoint, the researcher’s choice between stationary or unit-root behavior will have an effect on the inferences that can be drawn from any model that includes the variable. Treating the variable as a unit-root process leads the researcher to transform it through the process of differencing, that is, generating a new series based on the differences between consecutive time points. However, this transformation is not benign as it prohibits the researcher from identifying any long-term relationships between the differenced variable and other variables in the model (Box and Jenkins 1970; McCleary and Hay 1980; Norpoth 1993; Hamilton 1994; Enders 1995). Leaving a variable in level form avoids this problem but still can have negative consequences if the data generating process (DGP) of the variable does indeed possess some degree of long-memory. Specifically, spurious regressions - finding a significant relationship between variables where none truly exists - are a likely result when variables with some degree of persistence are left in level form (Granger and

Newbold 1974; Lebo, Walker, and Clarke 1998b).

The introduction of fractional dynamics provides social science researchers with an opportunity to avoid this forced dichotomy. By questioning the duality of stationary processes versus random walks, political scientists are finding that variables need not be strictly classified as integrated of order zero (I(0)) or of order one (I(1)) (Box-Steffensmeier and Smith 1996). Indeed, between these two extremes lies the possibility that a series may be fractionally integrated, where $0 < I < 1$. Over infinite periods, a fractionally integrated series will be mean reverting but over finite periods, it will mimic the properties of a unit-root series. Given that political scientists work with finite data sets with relatively few time points, the importance of understanding the properties of near- and fractionally-integrated time-series may be appreciated.

The use of fractional integration techniques has several attractive features. First and most important is an ability to develop models that more accurately mimic the data generating processes of the variables involved. Expecting a DGP to possess either perfect memory, memory that declines quickly at a constant rate, or no memory whatsoever implies a leap of faith avoided by allowing for the possibility that the degree of integration falls between zero and unity. Second, knowing that data have been properly (rather than over- or under-) differenced allows more confidence in regression results by minimizing the chances of spurious regressions. Lebo, Walker, and Clarke (1998b) demonstrate that finding a significant (.05) relationship between two variables may be as much as 15 times more likely when fractionally integrated variables are left in level form and included in regressions.

Third, moving from Autoregressive Moving Average (ARMA) or Autoregressive Integrated Moving Average (ARIMA) models to Autoregressive Fractionally Integrated Moving Average (ARFIMA) models by including the fractional differencing parameter, *d*, often will lead researchers to adopt more parsimonious specifications as they drop cumbersome moving average and autoregressive parameters that have been included in their models to approximate fractional dynamics (Hamilton 1994, p. 449; Lebo, Walker, and Clarke 1998a). Fourth, fractional, rather than integer, differencing guards against the questionable practice of over-differencing (DeBoef and Granato 1997).

Fifth, and finally, understanding that a series is fractionally integrated has significant theoretical implications. For example, as will be discussed, Key's (1966) explanation that some voters are "stand-patters" while others are "switchers" (see also Converse, 1964) is consistent with finding that aggregate measures of partisanship are fractionally integrated. This follows from Granger's (1980) aggregation theorem as "macropartisanship" is computed by aggregating individuals with various autoregressive patterns. Thus, DGPs may become more comprehensible when we are willing to entertain a wider range of behavior at the micro-level. Recognition of the significance of each of these five features motivates this dissertation. Various procedures for the incorporation of fractional dynamics into bivariate and multivariate time-series models are first developed and then demonstrated with a model of governing party support in Britain and a model of presidential approval in the United States. The remainder of this chapter places the problem of fractional integration within the development of the field of time-series analysis.

1.2 A History of Time Series and Popularity Functions

Although the study of politics and economics were often inseparable during much of the 19th century, studies of political economy entered a hibernation period for much of the 20th century (Heilbroner 1972; Clarke, et al. 1992). However, this situation has changed over the past quarter century as new interest in the relationship between economics and politics has brought political economy back as a major field within political science. Clarke, et al. (1992) propose that one reason for this renewed interest is the increased involvement by governments in their national economies in the wake of the Keynesian revolution in macroeconomic management (see also, Stewart 1986). The faith of political parties in Keynesian techniques led them to assure voters that they could manage the economy effectively and provide continued prosperity (Clarke, et el. 1992). In turn, this encouraged voters to hold parties accountable for fluctuations in personal and national economic health. Through these enhanced expectations, politics and economics grew ever closer and, when the surging post-war western economies grew stagnant in the 1970s, public discontent with the economy became synonymous with their discontent for their governments.

At the same time as these real world factors brought together the topics of politics and economics, advances in political science sought the same result. The introduction to political science of the rational choice approach which is concerned with the utility based decisions of rational, self-interested individuals refocussed the direction of many researchers and quickly permeated the discipline (Downs 1957; Keech, Bates and Lange 1989; Clarke, et al. 1992). Rational choice theory has had a particularly strong impact on the area of voting behavior, supplanting the University of Michigan's social-psychological approach as the dominant paradigm (e.g., Campbell et al., 1954, 1960). The economic theories of the rational self-interested voter developed by Downs (1957) and elaborated upon by Key (1968) have led to an explosion of research on electoral choice (e.g. Kinder and Kiewet, 1979; MacKuen, Erikson, and Stimson 1992; Sanders 1991; Clarke and Stewart 1994, 1995). These changes in real-world politics and economics coupled with a new intellectual focus have led researchers to study the relationships between each of objective economic conditions - such as unemployment and inflation - and subjective financial evaluations, and support levels for political parties and party leaders (Clarke, et al., 1992). Incorporating data on these items into models of political support, researchers have improved their ability to explain and predict election outcomes as well as the dynamics of party support between elections.

Thus, a great deal of research has been concerned with the development of "popularity functions" (Clarke, et al. 1992). Aggregating individual-level responses gathered from opinion polls between elections, popularity functions model the factors that affect levels of political support (e.g., Sanders 1992;

Clarke and Stewart 1994). Among these factors are political and economic events, economic sentiments, and leader support levels. In terms of economics, subjective measures have supplanted objective measures such as unemployment and inflation as the keys to understanding the links voters make between economics and politics (MacKuen, Erikson, and Stimson 1992). Indeed, subjective measures such as the University of Michigan Index of Consumer Sentiment are useful because they isolate voters' perceptions of economic conditions.

Despite the widespread acceptance of the importance of subjective economic evaluations, two important controversies exist among researchers. The first concerns whether voters emphasize their own self-interest or the state of the national economy when they form their political preferences (Clarke, et al. 1992). Kinder and Kiewet (1979, 1981) demarcate these attitudes as "egocentric" and "sociotropic" evaluations, respectively. Downs' (1957) theories of the rational self-interested voter would suggest that egocentric measures are far more important than sociotropic measures. Nevertheless, sociotropic evaluations often have been found to be important predictors of voting intentions (MacKuen, Erikson, and Stimson 1992).

A second controversy exists between those who favor prospective evaluations and those who favor retrospective ones, that is, whether voters are more concerned with the past or the future. Key's (1966) assertion that incumbents will be rewarded or punished by voters according to the state of their pocketbooks is clear support in favor of the retrospective thesis. This is entirely rational from a Downsian perspective because retrospective voting allows the voter to consider “one actual present utility income and a hypothetical present one” rather than merely “two hypothetical future utility incomes” (1957: 40). Clarke et al. (1992: 8) elaborate on the rationality of favoring retrospective evaluations pointing out that if the rhetoric of all parties can be discounted on the assumption that parties will say anything in their quest for victory, the only trustworthy information available to voters is past performance.

However, “Bankers” models question the rationality of retrospective voting. From this perspective, the rational voter understands that what is past is past and thereafter muddles through party rhetoric in search of which party offers the best hope for a prosperous future. Past party performance will remain informative to voters as they use it to judge parties’ ability to implement their promises. In this sense, prospective evaluations are inextricably bound to retrospective ones (Clarke, et al. 1992).

Research that compares the relative explanatory utility of prospections versus retrospections and egocentric variables versus sociotropic ones has been plagued by methodological problems. Of particular interest here are the problems that arise when one uses aggregate time series data. The use of aggregate data collected on a regular basis does provide students of political dynamics with a wealth of time points compared to the use of individual-level panel data. However, despite their usefulness for studying dynamic relationships, time-series variables created by aggregating individual-level data may threaten inferences if dealt with improperly.

Early attempts to construct popularity functions, such as Mueller (1970), implicitly assume data to be stationary by leaving it in level form prior to multivariate analyses. Granger and Newbold (1974) point out the pernicious consequences that occur when data that are non-stationary are treated as if they were stationary. Specifically, spurious regressions are likely to occur because the non-stationary pattern of one variable may appear to cause the same characteristics in the other. Thus, more sophisticated techniques need to be employed to guard against these threats to inference.

Over the past quarter-century, political methodologists have familiarized themselves with Box-Jenkins ARIMA techniques (Box-Jenkins 1970) and VAR models (Sims 1980). These new techniques challenged OLS regression as the method of choice for the analysis of time series data. Although these techniques are useful, they are insufficient to guard against spurious regressions if the question of stationarity is not properly addressed. Some modelers such as MacKuen, Erikson, and Stimson (1992) have used autoregressive distributed lag models in an attempt to circumvent the pitfalls of using non-stationary data in level form.[1] Analysts such as Clarke and Stewart (1994) question the efficacy of this latter approach and use the concepts of cointegration and error correction models as means of modeling the long-term dynamics of non-stationary series. Despite these advances, the recent introduction of the concept of fractional integration to political researchers necessitates reexamination not only of the conclusions derived from earlier studies but also of the data themselves and the estimation procedures used to analyze them.

1.3 Time Series Methodology and Fractional Dynamics

The concept of fractional dynamics may be usefully thought of as a generalization of the familiar ARIMA models (see Box and Jenkins 1970; McCleary and Hay 1980; Hamilton 1994; Enders 1995). The result is an ARFIMA model where the data generating process for series X is described as follows,

$$\phi(B)(1-B)^d X_t = \theta(B)\epsilon_t \qquad \text{where: } \epsilon_t \sim N(0,\sigma^{2)} \qquad (1.1)$$

In Equation (1.1) B represents the backshift operator such that $B^k\epsilon_t = \epsilon_{t-k.}$ Further, $\phi(B)$ represents stationary autoregressive processes and $\theta(B)$ represents stationary moving-average processes. The degree of integration for X is measured by the fractional differencing parameter, *d*.

Traditional approaches to time-series analysis assign integer values to *d* in (1.1) (e.g. Box and Jenkins 1970; McCleary and Hay 1980). For the case where *d*=0, the series will be characterized by mean reversion, finite variance and covariance stationarity and can be adequately modeled using combinations of autoregressive and moving average parameters (ARMA (p,0,q) models, see Figure 1.1). The special case of the random-walk, where *d*=1 (see figure 1.5), is characterized by mean, variance, and covariance non-stationarity (Sims and Uhlig 1991; Durr 1993; Ostrom and Smith 1993; Box-Steffensmeier and Smith 1998). By wholly differencing, the random-walk series can be modeled using stationary autoregressive and moving-average parameters in an ARIMA (p,1,q) format.

Recognizing that the value of *d* may lie between 0 and 1 and realizing the diversity of characteristics in this middle ground motivates fractional integration methods. As with a series where $d=0$, a series where $0<d<1$ will be mean reverting. However, a series will cease to be variance and covariance stationary where $.5<d<1$ (Baillie 1996:22). Figure 1.2, 1.3, and 1.4 show various fractionally integrated series where *d* equals 0.25, 0.5, and 0.75, respectively.

Of critical importance is the fact that a fractionally integrated time-series will behave in a distinctly different manner than will a series where *d* holds an integer value. Specifically, the fractionally integrated series will be long-memoried with significant - though not necessarily strong - correlations existing between distant time points. It is important to distinguish this type of series from a so-called near-integrated series, a series that is highly autoregressive and for whom significant correlations at long lags will also exist. The key difference between the two is that the long-memory of a near-integrated series declines steadily at an exponential rate while that of a fractionally integrated series may decline more slowly. Indeed, significant and steady correlations across long lags visible in its autocorrelation function is the signature characteristic of fractionally integrated series (Lo 1991: 1286). Over a great many time-points, the memory of a fractionally integrated series thus may be more persistent than that of a near-integrated series. Hence, memory may fade at a rate that is neither exponential nor constant.

1.4 Fractional Differencing

Aside from being less restrictive than a modeling technique where *d* is confined to integer values, the ability to model memory in a wider variety of ways seems a more reasonable method to mimic unknown data generating processes. Indeed, using the ARFIMA format, the short-term dynamics of autoregressive and moving average parameters are complemented by the complex long-term dynamics of *d*. In order to properly model a fractionally integrated series, we need to be acquainted with the concept of fractional differencing (Granger 1980; Hosking 1981).

When confronted with a series that is a unit-root, the standard procedure is to create a new "differenced" series based on the changes from one period to the next in the original variable. By doing so, the problems of non-stationarity exhibited in the original series are eliminated and the new series can be modeled using stationary ARMA components only. However, for a series where the level of integration lies between 0 and 1, creating a series based on the differences between time points will "over-difference" the series. That is, it will not create a white-noise ARMA series but, rather, will create an ARFIMA series for which $d < 0$. Thus, rather than apply the usual differencing procedure of (1-B), we wish to difference the series only by *d*, the true level of integration. That is, the value of each point in the fractionally differenced series should be based only on the proportion of the previous time point remembered in the present.

Granger's (1980: 288) explanation of the fractional differencing procedure is helpful in conceptualizing what the new series will look like. Granger imagines "a filter $\alpha(B)$ such that when used twice, one gets the usual difference, i.e. $\alpha(B)^2 = (1-B)$." Applying this filter twice, we are thus wholly differencing in the traditional fashion. However, by applying the filter only once, we are merely "half-differencing," exactly what we would want to do to turn a d=.5 series into a stationary white-noise process. Depending on our conception of $\alpha(B)$ we can filter our original series to obtain a d=0 white-noise series, regardless of whether d in the original series is a whole number or not. Conceptualizing the fractional integration filter as some factor of (1-B) is especially helpful when we see how fractional dynamics arise.

1.5 The Origins of Fractional Dynamics

Recently, researchers have demonstrated the commonality of fractional dynamics for political variables. Box-Steffensmeier and Smith (1996, 1998) find the quarterly macropartisanship index (MacKuen, Erikson, and Stimson 1989), the percentages of Democrat and Republican identifiers in quarterly Gallup polls, and the University of Michigan index of consumer sentiment are integrated of orders between zero and one. Lebo, Walker, and Clarke (1998a) analyze 17 popular political time-series including U.S. presidential approval, U.S. Supreme Court decision making in economics and civil rights cases, and domestic policy mood (Stimson 1991) and find fractional dynamics to be at work in the DGP of nearly all their variables. The fact that so many variables across several areas of inquiry in political science follow similar patterns is less surprising when we realize what these variables have in common. Indeed, all of these variables are aggregate measures of individual-level behavior, precisely the type of data likely to be characterized by fractional dynamics (Granger 1980).

Granger (1980) demonstrates that fractional dynamics are built into a series when it is created by aggregating heterogenous individual-level behavior.[2] Heterogeneity here refers to individuals' possession of various degrees of autoregressive and moving-average behavior. Granger explains a series x_{jt} consisting of individuals j = 1,2,...,n each with their own autoregressive parameter, α_j, randomly generated from a beta distribution (0,1). Equation (1.2) shows this series.

$$x_{jt} = \alpha_j x_{t-1} + \epsilon_t \quad \text{where } \epsilon_{jt} \sim N(0,\sigma^2) \tag{1.2}$$

Aggregating these autoregressive tendencies will create a series that is fractionally integrated, that is it will long remember the behavior of individuals for whom α approaches or equals unity but will quickly forget the past behavior of those with less pronounced autoregressive tendencies. The distribution of α for each j between zero and one will determine the fraction by which the series is integrated.

In the social sciences, Blumen, Kogan and McCarthy (1955) were the first to identify this phenomena. Their book, *The Industrial Mobility of Labor as a Probability Process* presented the now famous "mover-stayer" model. This posits that between periods, some workers - the "movers" - will move from one industry or plant to another while some workers - the "stayers" - will remain in place. However, the movers switch back and forth and their distribution will ultimately tend to some mean level in accord with industry or plant capacity. A measure of the percentage of workers in one industry or plant will aggregate these individual-level heterogenous behaviors and, as Granger (1980) warns, will thus be characterized by fractional dynamics.

Using standard practice, we would need to suppose that a given measure will have either perfect memory (I=1), no memory whatsoever, or perhaps some type of exponentially declining memory if it contained some autoregressive or moving-average process. However, in the mover-stayer model, we see that choosing the order of integration to be either zero or one is impossibly restrictive. A measure created by aggregating the behavior of workers will contain the behavior of the movers and the stayers at every time point. Some part of this aggregated series will have very long memory, remembering at any point the behavior of the stayers many periods ago. At the same time, another portion of the series will have no memory as the stochastic decisions of the movers are independent of their status in previous periods. Further, during each period, some stayers will be replaced in the industry's population by either new stayers or by movers. Likewise, movers may be replaced by new movers or by stayers. Through this slower process of population replacement, the effects of many periods ago eventually fade. Nevertheless, as long as a single individual in the sample stubbornly refuses to change over time and as long as another member of the sample continues to make decisions independent of his/her own past behavior, the series will continue to be fractionally integrated. This fact is especially relevant when one realizes the applicability of the mover-stayer model to many political phenomena (e.g. Converse 1964; Clarke and McCutcheon 1998).

Indeed, it may be hypothesized that political attitudes and behavior often will conform to the general pattern of the mover-stayer model. The popular "macropartisanship" variable is a good example. MacKuen, Erikson, and Stimson (1989) calculate macropartisanship as the percentage of Democratic identifiers out of all respondents who identify themselves as either Democrats or Republicans. As such, the variable aggregates individual-level decisions to form a single variable designed to describe trends in partisanship. By modeling macropartisanship in level form with neither autoregressive nor moving-average parameters, MacKuen, Erikson, and Stimson imply that the variable is devoid of any memory.[3] If this were true, knowing the value of macropartisanship in any given month would be irrelevant to any estimate of what value the variable will hold in the next month. We would simply infer that macropartisanship is wholly based upon exogenous factors and, *ceteris paribus*, behaves stochastically.

On the other hand, MacKuen, Erikson, and Stimson would still not have been correct had they instead chosen the conventional alternative of diagnosing and treating macropartisanship as a unit-root. Disaggregating the unit-root hypothesis implies perfect autoregressive behavior at the individual level, a situation that may describe some of the population, but certainly not all. In such a case, all else equal, individual partisanship will never change - an assumption directly opposed to that of the stationarity hypothesis. Further, the effects of a shock to a unit-root variable will be permanent as long-term swings preclude the variable from tending to some mean level. Thus, given the conclusions implicit in modeling decisions, researchers must be careful to ensure that their modeling techniques properly describe the underlying data generating process. The use of fractional dynamics makes this considerably more feasible.

However, including fractional dynamics in models becomes more complicated when one moves from the univariate case to the multivariate one. Although a great deal of work has been done on the study of fractional integration, very little has been done to inform political scientists of how to include ARFIMA components in complex multivariate models. Lebo, Walker, and Clarke (1998b) demonstrate the possibilities of spurious regressions when fractionally integrated series are left in level form and included in bivariate regressions. However, while showing the threats to inference posed by fractional integration, these authors do not offer an alternative course of action for dealing with the problem. This dissertation demonstrates how fractionally integrated time-series can be included in multivariate models of political behavior and illustrates the utility of doing so.

1.6 Organization of the Study

This dissertation is composed of six chapters that investigate techniques for developing models that include fractionally integrated time-series. Chapters II and III use Monte Carlo methods to investigate possible threats to inference posed by including fractionally integrated series in bivariate and multivariate regressions. Chapter II describes the results of Monte Carlo experiments which randomly generated two fractionally integrated series, transformed one or both of the variables, and then regressed one upon the other. Chapter II addresses the implications of both over- and under-differencing and finds that each of these operations makes regression results questionable. It is found that by fractionally differencing each of the two variables in a bivariate regression, estimates become quite trustworthy.

Chapter III extends the Monte Carlo experiments of Chapter II by adding independent variables with various time-dependent characteristics and experimenting with different ways of transforming these variables. Again, fractional differencing is found to be an important tool to ensure that expected regression results are not confounded. Taken together, the results in Chapters II and III demonstrate that the problem of fractional dynamics can easily be dealt with provided that one is capable of determining the level of integration of a given set of variables and then fractionally differencing them.

Chapter IV applies the results of the first two chapters to a model of governing party support in Great Britain. A discussion of the micro-foundations of measures of governing party support is used to explain why Conservative support and prime ministerial approval between 1979 and 1996 should be fractionally integrated. Indeed, numerous tests of stationarity and estimates of the *d* parameter show each of the two series are fractionally integrated with prime ministerial approval possessing nearly the memory of a unit-root. After fractional differencing, these variables are included in models that compare the utility of various types of subjective evaluations of economic performance in predicting support for the Conservative Party over the 1979-96 time period. Chapter IV also introduces the concept of fractional co-integration to political science after demonstrating that traditional approaches to error correction mechanisms are inappropriate with the presence of long memory in the equilibrium term. Chapter IV argues that while fractional integration techniques do not substantially alter the results obtained by more traditional methods, they are preferable for several reasons. Among these are improved model diagnostics and coefficient estimates as well as the simultaneous ability to mimic more accurately the DGP of the variables involved and reduce the possibility of spurious regressions.

Chapter V applies fractional integration techniques to a model of presidential popularity in the United States for the years 1978 to 1997. Again, various subjective economic evaluations are compared in rival models of presidential approval. The results obtained from the multivariate ARFIMA models support the findings of Clarke and Stewart (1994) who find that evaluations of future national prospects outperform personal prospections, personal retrospections and national retrospections as predictors of presidential approval. Chapter V also investigates the use of dummy variables in multivariate ARFIMA models.

Chapter VI concludes the dissertation and establishes an agenda for future research. A summary of the process by which researchers should evaluate and deal with the problem of fractional integration in their models is presented. The benefits of these methods are discussed at length with particular attention being paid to the ability of ARFIMA models to provide researchers with a common analytical framework. By beginning with the equation: $\phi(B)(1-B)^d X_t = \theta(B)\epsilon_t$ and thus allowing the order of integration to vary beyond integer values, ARFIMA modeling follows the directives of Hendry (1995) and others of the "LSE school" of econometrics (Gilbert 1986, 1989; Davidson and MacKinnon 1993) who insist researchers must begin with the most general model and "test, test, test" until reaching the more specific and parsimonious approximation of the data generating process. Using tests of stationarity and estimates of the value of *d*, researchers working separately can each approximate the true characteristics of DGPs and thus pave the way for greater consensus regarding the appropriate model specification.

Endnotes

1. Using Monte Carlo analyses, Lebo, Walker, and Clarke (1998b) find that while the use of a lagged endogenous variable does mitigate the problem, spurious regressions can still occur at 3-4 times their normal rate when data are fractionally integrated.

2. Granger explains that a fractionally integrated series may also be created by aggregating variables with dynamic relationships at the individual level. Further, a series will be fractionally integrated if its error term contains fractional dynamics.

3. Aggregating a panel survey in such a way would imply that as T approaches infinity, the partisanship of every respondent will at some point change. However, with the sample varying from one time point to the next, it is impossible to make such an inference.

CHAPTER II

FRACTIONALLY INTEGRATED TIME SERIES IN BIVARIATE REGRESSIONS: A MONTE CARLO ANALYSIS

2.1 Introduction

Although the topic of fractional integration has been discussed in the economics literature since Granger (1980), its ability to aid political researchers in their construction of complex dynamic models has been suggested only recently. Box-Steffensmeier and Smith introduce many political scientists to the problem of fractional integration in their 1996 *American Political Science Review* article, "The Dynamics of Aggregate Partisanship." Following Granger's (1980) explanation that the aggregation of heterogenous individual-level behavior would produce a series that is fractionally integrated, Box-Steffensmeier and Smith alert researchers to the possibility that data used by political scientists may be plagued by fractional dynamics. Indeed, the authors demonstrate that the popular political variables macropartisanship and the index of consumer sentiment (ICS) are each fractionally integrated. Investigating the univariate properties of a much greater variety of time-series including the ICS and its components and measures of U.S. Supreme Court liberalism, Lebo, Walker, and Clarke (1998a) confirm that many time-series used by political researchers are indeed fractionally integrated.

While understanding the univariate characteristics of political variables is valuable, recognizing the consequences of fractional dynamics should cause concern among researchers who use time-series methods to understand political relationships. Specifically, the possibility that regression results may be spurious when the value of *d* for either or both of the independent and dependent variables diverges from zero necessitates the re-examination of many models. Spurious, or “nonsense” regressions occur as the presence of serially correlated errors invalidate traditional methods of inference for regression (e.g., Yule, 1926; Phillips, 1986). As Granger and Newbold (1974) demonstrated in Monte Carlo experiments, tests of significance are seriously biased towards rejection of the null hypothesis of no relationship when unit-root series are included in bivariate regressions. Secondary problems of unit-root regressions include high R^2 and highly correlated residuals indicated by low Durbin-Watson statistics (Phillips, 1986).

However, the problem of spuriousness is not confined to regressions involving unit-roots. DeBoef and Granato (1997a) perform Monte Carlo experiments on series that are near-integrated and again find the problem of spuriousness to be rampant. In cases where the auto-regressive parameters of their two simulated variables approached unity, rejection rates of the null hypothesis are 69%, nearly 14 times as frequent as chance would allow in the absence of serial correlation when using significance tests with p=.05. Marmol (1995) extends Phillips’ analysis by analytically demonstrating that the likelihood of spurious regressions increases as *d* diverges from zero even when *d* is not confined to integer values.

Monte Carlo experiments employed by Lebo, Walker, and Clarke (1998b) confirm the huge problem spurious regressions pose for analysts using fractionally integrated data. They find that rejection rates soar as high as 72% in bivariate regressions where d =.9 for each of the variables and T= 100 (see Table 2.4). In support of Phillips (1986) and Marmol (1995), Lebo, Walker, and Clarke (1998b) also find rejection rates to increase along with the size of T. Even with the inclusion of a lagged endogenous variable as an independent variable, a popular panacea for models with poor diagnostics, rejection rates were three to four times as high as chance would allow. Thus, a great deal of evidence exists that demonstrates the dangers of including in regressions variables for which $d > 0$.

Given this evidence it is clear that researchers must deal with the possibility of fractional dynamics if they wish to have confidence that the inferences drawn from their regression analyses are sound rather than "nonsense." Although the problem encountered by Granger and Newbold - spurious regressions from unit-root series - is easily fixed via the process of first-differencing, researchers have been slow to offer a solution for the fractionally integrated case. This and the following chapter attempt to fill this void. Confining attention to the bivariate case, this chapter uses simulated data to test a variety of methods to avoid spurious regression results when dealing with fractionally integrated data. After explaining how these simulations were performed and what results one should expect in the absence of a bias towards rejection of the null hypothesis, the Monte Carlo results are presented. These include tests of the efficacy of fractional- and unit-differencing as well as the option of leaving variables in level form.

2.2 Monte Carlo Simulations: Method and Control Simulation

Monte Carlo simulations are useful when one wishes to investigate the properties of a certain statistical method (Mooney 1997). Simulation methods are particularly helpful when statistical theory is weak or entirely lacking. By randomly generating data and invoking a statistical procedure repeatedly, the results can be compiled and one can judge the attributes of the method employed (Mooney 1997). With these empirical results, one can test existing theory or generate new hypotheses.

There are several steps in the Monte Carlo simulations presented below and each follows the same basic pattern. Using RATS' ARFSIM procedure, two series (Y_t, X_t) were randomly generated so that T = 150 and $d = 0.1$ for each.[1] Then, depending on the simulation, some data transformation was performed on either or both Y_t and X_t. Next, using ordinary least squares (OLS), the dependent variable Y was regressed on a constant and the dependent variable, X, and the following output was recorded: coefficient estimates, standard errors, R^2, and the Durbin-Watson statistic. This was repeated 1,000 times. Next, the d value for the simulated X series was increased by 0.1 and another 1,000 bivariate regressions were performed. After 10,000 regressions, the *d* value of the simulated Y-series was increased by 0.1 and the process was repeated until ultimately 100,000 regressions were estimated and 100,000 observations existed for each of the four statistics. For each regression result, the value of X's t-statistic was calculated and the number of times that the absolute value of t was greater than 1.96 was recorded for each set of 1,000 regressions. This number was the occurrence rate of type I errors, the frequency with which true null hypotheses of no relationship were rejected as false. At the .05 level of significance, we would expect roughly 50 type I errors per 1,000 regressions to occur by chance alone.

In order to judge the results we would expect under perfect conditions, a control simulation was performed. As was done for all the simulations, two series were randomly generated from a (0,1) Beta distribution.[2] However, for this control experiment, it was stipulated that each series would be mean, variance, and covariance stationary with d=0. For each of 100,000 regressions between these random series, the X-coefficients, X-standard errors, R^2, and Durbin-Watson statistic were recorded. The frequency of type I errors was also recorded. The results of this simulation conformed nearly perfectly to what we would expect based on probability. This indicates the acuracy of the ARFSIM procedure as well as providing a model with which to compare later simulation results.

Table 2.1 presents the summary statistics for the control simulation. The X-coefficients are normally distributed with a mean very near zero. The standard errors are normally distributed (skewness=0.24 and kurtosis=3.10) with a mean of 0.0822, an artifact of the sampling pool.[3] The Durbin-Watson statistic is normally distributed (skewness=-0.01 and kurtosis=2.96) with a mean of 1.999 indicating that on average no bias towards serial correlation in the error term existed. The R^2 statistics indicate, as they should, very little relation between the random X and Y variables. And, most importantly, type I errors occurred only 5,164 times out of 100,000 regressions, almost exactly the 5,000 we would expect to find at the .05 level of significance. Thus, as expected, when one stationary series is regressed upon another, spurious regressions occur roughly 1 in 20 times. Comparing the results of subsequent simulations to these will demonstrate the need for all variables to be d=0 in order to minimize the threats to inference.

2.3 Bivariate Simulations: The Case of Under-Differencing

Standard time-series techniques suggest that the most efficient way of including non-stationary variables in bivariate regressions is to first transform them so that d=0 for each. Though analysts are chiefly concerned with eliminating long-term trends in the dependent variable, leaving a fractionally integrated independent variable in level form may create its own threats to inference. Following a discussion of the hypotheses under investigation, results are presented indicating the efficacy of fractionally differencing both sides rather than under-differencing the independent variable. The three hypotheses are:

$H_{2.1}$: In bivariate regressions, fractionally differencing both the dependent and independent variables by their respective estimated *d* values produces spurious regressions less often that does fractionally differencing the dependent variable only while leaving the independent variable in level form. This can be expressed as:

$H_{2.1}$: for $(1\text{-}B)^{d(Y)}Y_t = a + b_1(1\text{-}B)^{d(X)}X_t + \epsilon_t$ and $(1\text{-}B)^{d(Y)}Y_t = a + b_2X_t + \epsilon_t$

b_2 will be statistically significant (.05) more frequently that will b_1.

To demonstrate the value of fractionally differencing both the dependent and independent variables, the following hypothesis also was tested:

$H_{2.2}$: In bivariate regressions, fractionally differencing both the dependent and independent variables by their respective estimated *d* values will produce spurious regressions 5% of the time at the .05 level of significance, i.e. at the same rate we would expect from two stationary variables. Hypothesis 2.2 can be expressed as:

$H_{2.2}$: for $(1\text{-}B)^{d(Y)}Y_t = a + b_1(1\text{-}B)^{d(X)}X_t + \epsilon_t$

b_1 will be statistically significant (.05) 5% of the time.

Also, the practice of fractionally differencing both sides was tested against the option of fractionally differencing the dependent variable and including the popular “cure-all” of a first-order auto-regressive parameter as an independent variable along with a fractionally integrated independent variable left in level form:

$H_{2.3}$: In bivariate regressions, fractionally differencing both the dependent and independent variables by their respective estimated *d* values produces spurious regressions less often than does fractionally differencing the dependent variable and including a first-order auto-regressive parameter as an independent variable along with an untransformed fractionally integrated independent variable. This can be expressed as:

$H_{2.3}$: for $(1\text{-}B)^{d(Y)}Y_t = a + b_1(1\text{-}B)^{d(X)}X_t + \epsilon_t$ and $(1\text{-}B)^{d(Y)}Y_t = a + Y_{t-1} + b_3X_t + \epsilon_t$

b_3 will be statistically significant (.05) more frequently than will b_1.

To test hypotheses 2.1-2.3, three sets of simulations were performed as described above. In Simulation 1, prior to each regression, the independent and dependent variables were fractionally differenced by the value of *d* built into each by the ARFSIM procedure. In Simulation 2, the independent variable was left in level form while the dependent variable was fractionally differenced as it was in Simulation 1. Simulation 3 was similar to Simulation 2 except for the inclusion of a lagged endogenous variable as an independent variable.

Simulation 1 Results

When both the dependent and independent variables were fractionally differenced by their assigned *d* values, the rate of spurious regressions was near perfect at 5,181 per 100,000, thus supporting Hypothesis 2.2. Table 2.2 breaks down these type I errors by each set of 1,000 regressions and demonstrates the value of fractionally differencing both sides. In only two of Table 2.2's 100 cells is the number of type I errors statistically distinguishable from the expected 50, again supporting Hypothesis 2.1.[4] Also, no pattern seems to exist that would indicate that fractional differencing gains or loses power as *d* varies between 0 and 1.

Looking more closely at the results of Simulation 1, we can see how the problem of bias towards nonsense regressions was overcome and thereby recognize the value of fractionally differencing both the dependent and independent variables. The Durbin-Watson statistics were normally distributed (skewness=-0.01 and kurtosis=2.99) with a mean of 1.9959. Standard errors were likewise normally distributed (skewness=0.26 and kurtosis=3.11) with a mean of 0.082, results nearly identical to those of the control experiment. R^2 values were consistently low and coefficient estimates averaged 0.0002 and were distributed normally. Thus, comparing the results obtained from Simulation 1 with those of the control simulation, it is evident that fractional differencing each side by its assigned value of *d* is sufficient to avoid the problem of spurious regressions. The next two simulations demonstrate that selectively applying the fractional differencing filter fails to negate this problem.

Simulation 2 & 3 Results

In Simulation 2, the dependent variable was fractionally differenced but the independent variable was left untransformed. Rejection rates of the null hypothesis of no relationship rose to nearly 5.5%. While this number is not alarmingly high, it does represent a 10% increase in the likelihood of finding a relationship between two variables when no such relationship truly exists. Table 2.3 shows that the occurrence rate for type I errors is statistically different from the expected 50 in 16 of 100 cells and that the frequency of these errors increases substantially as the independent variable crosses the $d = .5$ threshold and moves from variance stationarity to variance non-stationarity. Comparing these results with those of Lebo, Walker, and Clarke (1998b) in Table 2.4 we see that, although an imperfect procedure, fractionally differencing only the dependent variable vastly reduces the possibility of making a type I error. Thus, although the evidence from Simulation 2 supports Hypothesis 2.1 it does not do so overwhelmingly. An examination of the components of the t-statistic reveals the true problems with this approach.

Indeed, it is in the standard errors and coefficients estimated by Simulation 2 that the inadequacy of leaving the independent variable in level-from is demonstrated. Table 2.5 shows that the standard errors of the independent variable are biased downwards as the *d* value for X moves from 0 to 1. When $d > .7$, the mean value for the standard error is less than half of 0.082, its expected value under perfect conditions. The findings of Lebo, Walker, and Clarke (1998a) make this result especially relevant as they find most political variables in their inventory to have *d* values in the range of 0.7 to 0.9.

Table 2.6 shows that leaving the independent variable in level form also biases downward the absolute value of X-coefficients.[5] The fact that both standard errors and coefficients are moving in the same direction and at nearly the same pace as *d* grows accounts for the failure of spurious regressions to rise dramatically (remembering that t = estimate of b ÷ estimate of s.e.). Indeed, Figure 2.1 shows that, as far as rejection rates are concerned, this is a case of two wrongs making a right. Nevertheless, the decline in the standard errors due to time dependence in the error term is a bias worth avoiding. This is confirmed by Figure 2.2 which compares the skewed distribution of the standard errors (skewness=-0.28 and kurtosis=1.87) generated by Simulation 2 to the normally distributed standard errors of the control simulation (the solid line).

In order to ensure that these problems could not be solved by including a lagged endogenous variable, another simulation was performed. Simulation 3 was the same as Simulation 2 except for the inclusion of a first-order auto-regressive parameter as an independent variable. This addition, however, failed to overcome the threats to inference created by failing to fractionally difference the independent variable, X. In Simulation 3, 5,677 type I errors were made. Again, this number is not staggering but it is statistically different from 5,000 with 13.5% more spurious regressions than we would hope for at the .05 confidence level, thereby supporting Hypothesis 2.3. Further, as was seen in Simulation 2, standard errors and the absolute value of coefficients declined steadily as the value of *d* for X increased. As before, the simultaneous decline of standard errors and coefficients prevented an explosion of type I errors but nevertheless indicates the unwanted presence of autocorrelated errors (skewness=-0.52 and kurtosis=5.41 for the Durbin-Watson statistics) .

Thus, by comparing each of simulations 1, 2, and 3 with the control simulation, we can see the value of fractionally differencing both the independent and dependent variables prior to including them in bivariate regressions. In support of hypotheses 2.1, 2.2, and 2.3, it is evident that fractionally differencing Y while leaving X in level form increases the number of spurious regressions by a statistically significant, albeit not overwhelming, number. These simulations also demonstrate that fractionally differencing each of the variables avoids biasing downwards standard errors and coefficients as *d* increases for X. Indeed, regardless of the respective values of *d* for Y and X, fractionally differencing both prior to regression yields results identical in all respects to those obtained by using stationary variables where *d*=0. Next, the value of fractional differencing again will be supported as additional simulations demonstrate the consequences of over-differencing.

2.4 The Case of Over-Differencing: Analytical Results

Having demonstrated the consequences of assuming no long-term memory in the presence of long or permanent memory, the alternative of incorrectly assuming the presence of permanent memory is now investigated. While researchers have spent a good deal of time considering the threats to inference posed by under-differencing (e.g., Granger and Newbold, 1974; Phillips, 1986; Marmol, 1995; DeBoef and Granato, 1997a; Lebo, Walker, and Clarke, 1998b) very little attention has been given to the consequences of over-differencing (DeBoef and Granato, 1998b being one exception). This lack of interest is quite surprising given the frequency with which first-differencing is used and given the precarious nature of the implicit assumption of first-differencing, that the original series must contain perfect (*d*=1) memory. When this assumption is incorrect and *d* < 1, first-differencing will create a series with *d*

< 0.

A series of this type is typified by negative auto-correlations in the error term and inferences based on the differenced series lose credibility (DeBoef and Granato, 1997b: 3). While DeBoef and Granato (1997a) found that no serious problems arose from over-differencing near-integrated ($\phi \geq 0.8$) data, the discussion below outlines the possible consequences of including in bivariate regressions fractionally integrated series that have been over-differenced.

Indeed, several problems are likely to arise when either or both the dependent and independent variables are over-differenced. As mentioned above, an over-differenced series, ΔY_t, will be characterized by auto-correlated errors. The presence of this problem is readily apparent as it serves to inflate Durbin-Watson values. Further, when modeling ΔY_t, either in univariate ARIMA form or with the addition of an exogenous independent variable, the inclusion of a moving-average parameter is likely to be necessary to mimic the error term's built-in auto-correlation.

To explain this phenomenon simply, the univariate case where *d* is constrained to integer values in a (0,*d*,0) model is presented:

begin with the DGP:

$$Y_t = \phi Y_{t-1} + \epsilon_t \qquad \text{where: } \epsilon_t \sim N(0,\sigma^2) \qquad (2.1)$$

Suppose Y_t is stationary and therefore the true value of $\phi = 0$, but we mistakenly believe Y_t to be a unit-root, i.e. that $\phi = 1$.

We would then proceed to difference Y_t to obtain ΔY:

$$Y_t - Y_{t-1} = (\phi Y_{t-1} + \epsilon_t) - (\phi Y_{t-2} + \epsilon_{t-1}). \qquad (2.2)$$

Replacing ΔY_t for Y_t - Y_{t-1} and substituting in the true value of ϕ, we have:

$$\Delta Y_t = \epsilon_t - \epsilon_{t-1} \qquad \text{where: } \epsilon_t \sim N(0,\sigma^2) \qquad (2.3)$$

Here ϵ_t is a stationary white noise process and ϵ_{t-1} represents a non-invertible moving average process with θ = -1 (see Enders 1995: 97). The presence of a non-invertible moving-average parameter defies explanation in a theoretical sense and also wreaks havoc on estimation procedures.[6] Further, for bi- or multivariate purposes, the addition of an independent variable will not mitigate these effects. While the error of over-differencing is seldom committed to the extent where d=-1 for the differenced series, problems quickly mount as a series diverges downwards from d=0.

DeBoef and Granato expand (2.2) and demonstrate that first-differencing a near-integrated series will also build a moving-average process into the series. The same can be said for the long-memoried, fractionally integrated series. Again using the univariate case and temporarily ignoring the short term auto-regressive and moving-average parameters, the case where d is no longer constrained to integer values is presented:

Begin with the DGP of pure fractional noise:

$$(1-B)^d Y_t = \epsilon_t \qquad \text{where: } \epsilon_t \sim N(0,\sigma^2) \qquad (2.4)$$

now isolate for Y_t and apply first differencing

$$Y_t - Y_{t-1} = (1-B)\epsilon_t / (1-B)^d$$

$$= (\epsilon_t - \epsilon_{t-1}) / (1-B)^d$$

thus,

$$\Delta Y_t = \epsilon_t/(1-B)^d - \epsilon_{t-1}/(1-B)^d \qquad (2.5)$$

First differencing Y_t will be appropriate when $d = 1$ and (2.5) thereby reduces to:

$\Delta Y_t = \epsilon_t$.

However, we are again left with a non-invertible moving-average process for the case where $d = 0$ and (2.5) reduces to:

$\Delta Y_t = \epsilon_t - \epsilon_{t-1}$.

When a fractionally integrated variable ($0< d < 1$) is first differenced, a moving-average parameter equal to $1/(1-B)^d$ will be built into the series. This will be the case whether we wish to model the variable in univariate, bivariate or multivariate form.

Aside from the creation of moving-average processes, the act of over-differencing is expected to cause other problems as well. The most obvious problem stems from the fact that two over-differenced series will have at least that aspect in common. As such, their inclusion in a bivariate regression may lead one to conclude more often than chance would allow that the DGP of one variable is explicable by the DGP of the other. Thus, spurious regressions are again expected to plague regressions that use two over-differenced variables.

2.5 Bivariate Simulations: The Case of Over- Differencing

Given the analytical results, it was expected that over-differencing variables prior to their inclusion in bivariate regressions would cause several problems and it was further expected that these problems would be magnified as the original value of *d* declined thereby increasing the degree of over-differencing. Three hypotheses below address these anticipated problems. After stating these hypotheses, Monte Carlo evidence is presented which demonstrates the threats of over-differencing and thereby again underscores the value of fractional differencing. The first of the three hypotheses is:

$H_{2.4}$: In bivariate regressions, first-differencing both the dependent and independent variables will lead to spurious regressions more often than the 5% of the time chance would otherwise allow. This can be expressed as:

$H_{2.4}$: for $(1\text{-}B)Y_t = a + b_1(1\text{-}B)X_t + \epsilon_t$ where d(Y) and d(X) < 1,

b_1 will be statistically significant (.05) more frequently than 5% of the time.

Next:

$H_{2.5}$: When $d < 1$ for the dependent variable, first differencing will introduce a statistically significant moving-average process into the DGP of the differenced series more frequently than the 5% of the time chance should allow. This can be expressed as:

$H_{2.5}$: for $Y_t - Y_{t-1} = a + b_1(1\text{-}B)^{d(X)}X_{t-1} + \theta\epsilon_{t-1} + \epsilon_t$ where d(Y) < 1

θ will be statistically significant (.05) more frequently than 5% of the time.

And, finally:

$H_{2.6}$: for $Y_t - Y_{t-1} = a + b_1(1\text{-}B)^{d(X)}X_{t-1} + \theta\epsilon_{t-1} + \epsilon_t$ where d(Y) < 1

θ will often be non-invertible when d(Y) is close to 0.

To test hypotheses 2.4-2.6, several sets of simulations were performed following procedures similar to those described above. Several additional simulations also were performed to explore the additional complications that can arise by from over-differencing. In Simulation 4 the dependent variable was first-differenced while the independent variable was fractionally differenced by its value of *d*. Simulation 4A was the same as Simulation 4 except that regressions included a moving-average parameter and were estimated using Box-Jenkins techniques rather than linear regression methods.[7] In Simulation 5, the dependent variable was fractionally differenced and the independent variable was first-differenced and OLS was used to estimate the regression. Simulation 5A added a moving-average parameter to the regression equation and used Box-Jenkins analysis rather than linear regressions. Simulation 6 first-differenced both the dependent and independent variables prior to the OLS regression. Simulation 6A added a moving-average component and switched to Box-Jenkins estimation. Simulation 6B was the same as Simulation 6 but added a first-order auto-regressive parameter as an independent variable. Finally, Simulations 6C, 6D, 6E, and 6F emulated Simulation 6 but investigated the impact of sample size on the threats to inference posed by over-differencing using sample sizes of 50, 100, 200, and 500, respectively.

Simulations 4 & 4A Results

In Simulation 4, the dependent variable was first-differenced while the independent variable was fractionally differenced rendering it $d = 0$. Although the rate of false rejections in this simulation was completely acceptable at 5,214 per 100,000, several negative consequences of over-differencing were evident. One such problem was with the standard errors and absolute coefficient values, each of which was biased upwards as the value of *d* for Y decreases. Their simultaneous rise accounts for the failure of this over-differencing exercise to increase the rate of type I errors. Also, as expected, negative auto-correlations in the error term were present as seen in the Durbin-Watson values of Table 2.7. Table 2.7 demonstrates that the negative auto-correlation becomes more serious as the degree of over-differencing increases. This negative auto-correlation is a strong hint at the validity of Hypothesis 2.5, and thus motivated another simulation that included a moving-average parameter.

Indeed, Simulation 4A clearly demonstrated the quirks that over-differencing can artificially build into a transformed series. Using the Box-Jenkins approach, the dependent variable, Y_t, was regressed on a constant, an independent variable, X_t, and a moving average parameter. As Table 2.8 shows, the moving-average parameter was statistically significant over 99% of the time for $d(Y) \leq 0.6$ and still significant over 69% of the time when $d(Y) = .8$, a popular degree of memory for political time-series (Box-Steffensmeier and Smith 1886; Lebo, Walker, and Clarke 1998a). The strength of the moving-average process is demonstrated by the absolute value of its coefficient which averaged .948, .547, and .118 when Y had been over-differenced by .9, .5, and .1, respectively. This is also evident in Table 2.9 which shows, as Hypothesis 2.6 posits, that non-invertibility of the moving-average parameter plagued the estimates where *d* approached zero. Combined, these results not only demonstrate the validity of Hypotheses 2.5 and 2.6, they show how over-differencing, even by .1 or .2 can seriously alter our perception of the DGP of the dependent variable.

Further, the results of Simulation 4A show that attempts to "model out" auto-correlation only serve to create further problems. Although with a mean of 1.871, Durbin-Watson values have fallen to manageable levels, as Figure 2.3 shows, the distribution of these values is a far cry from what it should be (skewness=-1.00 and kurtosis=4.09). Indeed, the mean value of the Durbin-Watson statistic only serves to mask the deeper problems created by over-differencing. First, by including a moving-average parameter, the standard errors of the independent variable were again biased downwards leading to a substantial increase in the number of type I errors (see table 2.10). Also, the presence of moving-average parameters that are strongly significant drastically increases R^2 values. Table 2.11 demonstrates the degree to which model fit improves over the mean R^2 value of .007 given by the control simulation. Though the independent variable here is no more related to the dependent variable than it was before, relatively larger R^2 values may ask us to believe our models are fairly sound.

Simulation 5 & 5A Results

As one might suspect, the havoc that over-differencing creates is greatly reduced when it is done to the independent rather than the dependent variable. With the dependent variable fractionally differenced as it was for Simulations 5 and 5A, regression results will seldom include the problem of auto-correlation in the error term and will thereby avoid the majority of the threats to inference observed in Simulations 4 and 4A. Although X's standard errors and coefficient values were biased downwards by over-differencing, spurious regressions occurred at an acceptable rate of 5.2 per hundred. Durbin-Watson values averaged 1.994, indicating that the addition to the equation of a moving-average parameter would only prove superfluous. Not surprisingly, this finding was confirmed by Simulation 5A, the results of which barely differ from those of Simulation 5.

Simulations 6, 6A, 6B, & 6C- 6F Results

For Simulations 6, 6A, and 6B each of the independent and dependent variables were first-differenced. These simulations are likely the most important ones performed as they mimic most accurately the standard operating procedures of political time-series analysts. Indeed, ARIMA researchers are compelled to use this technique for several reasons. The decision of whether to first-difference data has traditionally been answered by tests of stationarity, most notably the Dickey-Fuller test that tests a null hypothesis of a pure random walk or random walk with drift against the alternative hypothesis of stationarity (Dickey and Fuller, 1979).

Like many tests of stationarity, however, the Dickey-Fuller test pre-dates knowledge of fractional integration and has low power when confronted with fractionally integrated alternatives (e.g., Diebold and Ruderbusch, 1991). As a great many political time-series are characterized by long, yet finite, memory with *d* values approaching but not reaching 1, the Dickey-Fuller test and others like it often conclude that a given series is a unit-root and requires first-differencing (Lebo, Walker, and Clarke, 1998a). Since models of political relationships often include non-stationary - yet not quite unit-root - processes on both sides of their equations (see MacKuen, Erikson, and Stimson’s “macropartisanship," for example), over-differencing is often extended to the independent as well as the dependent variable. This latter fact is also ensured by the common "rule of thumb" in ARIMA modeling that what one does to the left-hand-side variable must be done to those on the right-hand-side as well (DeBoef and Granato, 1997a). Thus, while Simulations 4, 4A, 5, and 5A are informative, it is in the results to follow that we truly confront the nasty consequences political analysts create for themselves by over-differencing.

When both the dependent and independent variables were first-differenced (i.e., (0,1,0) ARIMA models), the number of spurious regressions increased substantially to the rate of 7,115 per 100,000. While these occurrences are a substantial improvement upon the horror show of Table 2.4 where rejection rates soar as high as 76%, they nevertheless represent a 40% degradation in the .05 confidence interval and occur often enough to support the validity of Hypothesis 2.4. Further, as Table 2.12 shows, nonsense regressions are an evident problem in 66 of the 100 cells and become more frequent as the degree of over-differencing increases. The roots of this increase are visible in X's standard errors (Table 2.13) and absolute coefficients (Table 2.14). Although both are simultaneously biased upwards, this bias affects the coefficients to a slightly greater extent and t-statistics thereby grow along with the degree of over-differencing. And, not surprisingly, negative auto-correlation in the error term is a large problem with an average Durbin-Watson value of 2.538 and a skewed distribution (skewness=-0.44 and kurtosis=2.42), shown in Figure 2.4. Although it is perhaps as bad as the disease, the cure to this auto-correlation is the addition of a moving-average parameter as was done for Simulation 6A.

In Simulation 6A's (0,1,1) models, the problem of auto-correlation has been improved but only at the cost of further obfuscating one's perception of the DGP. Figure 2.5 shows the modest improvement in the mean (1.874) and distribution of the Durbin-Watson statistic (skewness=-0.98 and kurtosis=4.06). As was seen in Simulation 4, Table 2.15 shows a significant moving-average parameter in nearly every case where the original dependent variable was variance stationary ($d < .5$). Increasing the degree to which the dependent variable has been over-differenced biases downwards the moving-average's standard errors while simultaneously biasing its coefficient upwards. As Tables 2.16 and 2.17 show, rather than the reduction of its standard errors, it is the explosion in the values of X's coefficients that accounts for the moving-average's often enormous t-statistics (Table 2.18) and the model's drastically improved R^2 values (Table 2.19). Even when a variable is over-differenced by as little as .1, moving-average parameters become significant more than 5 times as often as chance should allow. At the other end of the spectrum, over-differencing by .9 creates non-invertible moving average coefficients over one-quarter of the time. As Table 2.20 shows, support for Hypothesis 2.4 - that a significant increase in the rate of spurious regressions occurs as a result of over-differencing both sides of the equation - is not mitigated by adding a moving-average parameter to the estimated equation. Finally, the size of the spurious regression problem ranges from mild to serious as the *d* value of the pre-differenced Y crosses the 0.5 threshold and becomes variance stationary.

Next, Simulation 6B tested an over-differenced fractionally integrated dependent variable modeled in (1,1,0) form with a first-differenced independent variable. Durbin's h test values showed that the addition of the auto-regressive component is helpful in mitigating, though not quite eliminating, the problem of negative auto-correlation. Spurious regressions occur less frequently (Table 2.21) with X's standard errors and coefficients again biased from their expected values as the level of over-differencing increases. As was seen with the moving-average parameters, over-differencing introduces short-term dynamics into the series. Table 2.22 shows the high frequency with which the auto-regressive parameters are statistically significant especially where $d \leq -.5$ for the differenced series. Further, the high frequency of significant auto-regressive parameters contributes to inflated R^2 values. Finally, we can see that estimating the *d* parameter has the added advantage of being more parsimonious as (0,*d*,0) models simplify more archaic (1,1,0) models and thus conserve a degree of freedom.

One final set of bivariate simulations investigates whether sample size has an effect on the consequences of over-differencing. Each of the dependent and independent variable was first-differenced with sample sizes of 50, 100, 200, and 500 for Simulations 6C, 6D, 6E, and 6F, respectively. Increasing sample size was found to minimize the rate of spurious regressions which ranged from 7,325 for T=50 to 6,891 for T=500. This improvement, however, is unsatisfactory, especially given that so few political time-series can ever hope to attain 500 time-points. Indeed, a larger sample size does nothing to alleviate the problem of auto-correlation in the errors and Durbin-Watson values actually diverge further from 2 as T increases. Nevertheless, larger sample sizes were found to decrease the upwards bias on standard errors (Table 2.23) and thereby mitigate the problem of false rejections of the null hypothesis.[8]

2.6 Conclusion

The Monte Carlo experiments presented above clearly show that fractional differencing is the appropriate method of dealing with fractionally integrated data. With the ability of statistical packages such as RATS and OX to simply and quickly estimate the long-memory parameter *d* for a given series and then fractionally difference the series by that amount, the threats to inference posed by incorrectly differencing have become as unnecessary as they are drastic. Indeed, regardless of its original *d* value, fractional differencing creates a series with the same behavior as a stationary process, the same happy result as occurs when a unit-root process is first-differenced. Thus, when included in bivariate regressions, two fractionally differenced series are no more likely to appear to be related than are two stationary processes. The distribution of standard errors, coefficients, t-statistics, and Durbin-Watson statistics were the same for simulations which began with variables where d=0 as they were for those who required fractional differencing to achieve stationarity. Thus, fractional differencing is found to be vastly superior to the choice of under-differencing.

As demonstrated by Monte Carlo simulations, the traditional choice of first-differencing also presents serious threats to inference when variables fall in the range $0 \leq d < 1$. Among the negative consequences of over-differencing are: <u>upward bias of standard errors and coefficients, increased negative auto-correlation in the error term and an increased rate of false rejections of the null hypothesis</u>. It was shown analytically, as well as in simulation experiments, that first differencing a fractionally integrated series introduces artificial short-term dynamics into the transformed series. Although modleing these short-term dynamics in estimated equations mitigates the problems of over-differencing, it does so imperfectly and entails a loss of parsimony. In the next chapter, Monte Carlo experiments using simulated fractionally integrated time-series in multivariate regressions demonstrate that the value of fractional differencing extends to more complex models of time-dependent relationships as well.

Endnotes

1. A sample size of 150 was chosen because it is typical of time-series used by political scientists. Values for the simulated series were drawn from a (0,1) Beta distribution. The ARFSIM procedure was developed by Rob Schoen and is available through the Estima website. The procedure is based on the proposed method of Davies and Harte (1987) and is described in Beran (1994:215-17). See Appendix 1 for RATS programs and seed values.

2. The (0,1) Beta distribution was chosen so that the simulated series would closely resemble the type of political series under investigation here, i.e. aggregated and bounded on both ends with no known bias towards the normal curve. Choosing the (0,1) Beta distribution rather than the normal means that, holding *d* to zero, there is an equal probability of choosing any number between zero and one.

3. The values of the standard error estimates are only important relative to the values of the coefficient estimates. Since every time point in every one of the simulated series falls between zero and one, the average value for standard errors and absolute coefficients is quite low.

4. Each cell can be thought of as a sample observation of an entire population of t-statistics. The overall population is normally distributed and every twentieth individual has a t-statistic greater than 1.96 or less than -1.96. In order to judge if any of these observations are statistically distinguishable (.05) from the expected 50, a confidence interval is used as follows:

$\Pi = P \pm 1.96\ [(P(1-P))/n]^{1/2}$ where $P = .05$
simplified... $\Pi = .05 \pm .0135$
Thus, 95% of the observations should fall between 36.5 and 63.5 (see Wonnacott and Wonnacott, 1990; 273).

5. The absolute values of coefficients are used rather than simple coefficients because we are interested in the strength, not the direction of the relationship. Also, the use of absolute values keeps positive and negative values from canceling each other out when averaged.

6. The absolute value of a moving-average parameter must be less than 1 for invertibility. Non-invertible moving-average parameters cannot be estimated by Box-Jenkins techniques. The failure of Box-Jenkins estimation procedures to converge is often attributable to non-invertible moving-average processes (Enders, 1995).
Enders (1995, p. 97) explains with the following MA(1) model:

$Y_t = \epsilon_t - \theta\epsilon_{t-1}$ which can be expressed as: $Y_t / (1 - \theta B) = \epsilon_t$

or

$$Y_t + \theta Y_{t-1} + \theta^2 Y_{t-2} + \theta^3 Y_{t-3} + \ldots = \epsilon_t$$

If the absolute value of θ <1, Y_t can be represented by a finite-order AR process and estimation via the Box-Jenkins method is possible. However, if $\theta = 1$, the above becomes:

$$Y_t = -Y_{t-1} + Y_{t-2} - Y_{t-3} + \ldots$$

As such, the autocorrelations and partial autorelations between Y_t and Y_{t-n} will never decay - a factor upon which Box-Jenkins estimation relies. Enders (p. 97) further explains that "there is nothing 'improper' about a non-invertible model." The series Y_t implied by $Y_t = \epsilon_t - \epsilon_{t-1}$ is stationary with constant time-invariant mean, variance, and autocovariances. See also Hamilton (1994, pp. 64-68).

7. Moving-average parameters cannot be estimated using standard OLS procedures (Box and Jenkins, 1970).

8. These findings seem to contradict Phillips (1986), Marmol (1995) and Lebo, Walker, and Clarke (1998b) each of whom find that false rejections decreased as T increased. This discrepancy is likely due to the fact that each of those authors used series with positive *d* values while the over-differenced series of Simulations 6C-6F have negative *d* values.

CHAPTER III

FRACTIONALLY INTEGRATED TIME SERIES IN MULTIVARIATE REGRESSIONS: A MONTE CARLO ANALYSIS

3.1 Introduction

As Chapter II demonstrated, the fractional dynamics of each variable must be properly dealt with in order for models to yield unbiased and credible inferences. This fact, in conjunction with Box-Steffensmeier and Smith's (1996) and Lebo, Walker, and Clarke's (1998a) findings that fractional dynamics are extremely prevalent in political analysis, has serious implications for long accepted models of dynamic political relationships. A reexamination of the analyses in MacKuen, Erikson, and Stimson's 1989 article "Macropartisanship" in light of the findings of Box-Steffensmeier and Smith (1996, 1998), Lebo, Walker, and Clarke (1998a) and the Monte Carlo results of Chapter II reveals the need to reappraise dynamic models of political relationships.

In "Macropartisanship" MacKuen, et al. specify two time-series models. In the first, a quarterly measure of presidential approval is explained as a function of the Index of Consumer Sentiment (ICS), various political events such as Watergate and the Iranian hostage crisis, and presidential administration dummy variables (p. 1135). In their estimation of these relationships, MacKuen, Erikson, and Stimson opt for simplicity and keep their variables in level form which has serious consequences for the inferences they draw. Indeed, Lebo, Walker, and Clarke (1998a) estimate[1] *d* values for the quarterly ICS and presidential approval to be 0.91 and 0.89, respectively.[2] With a standard error of .068, Lebo et, al. reject the hypothesis of weak stationarity for both the ICS with t=13.37 and presidential approval with t=13.44.[3] Based on these results, it is clear that MacKuen, Erikson, and Stimson's use of these variables in level form is inappropriate. According to the Monte Carlo evidence of Lebo, Walker, and Clarke (1998b), the long-memory characteristics of the ICS and presidential approval make it 14 times more likely (71.5%) than chance would otherwise allow that MacKuen, Erikson, and Stimson would find a significant (.05) relationship between the two variables (p. 19). This increased likelihood of spuriousness was also present in their macropartisanship equation.

MacKuen, Erikson, and Stimson next explaine a level-form macropartisanship, the proportion of Democratic identifiers out of all identifiers of both parties, as a function of the Index of Consumer Sentiment, presidential approval, historic events, and administration dummies. Based on this model, MacKuen, Erikson, and Stimson conclude that macropartisanship responds quickly to changes in the independent variables implying that realignment is a continuing process based on perceptions of economic performance and the sitting president. However, a better understanding of the time series properties of the variables involved leads to different conclusions.

The DGP that generated the macropartisanship variable is certainly a textbook example of the type of process that will create fractional dynamics (Granger 1980; Box-Steffensmeier and Smith 1996, 1998). At the individual level, party identification switchers exhibit different autoregressive behavior than will party stayers. Aggregating these heterogenous behaviors to create the macropartisanship variable creates fractional dynamics in the aggregate time series data. The long-memory of the macropartisanship variable is first established empirically by Box-Steffensmeier and Smith (1996) who estimate a *d* parameter of .804 for the variable with a standard error of .057 rejecting the unit-root hypothesis (.01). The long-memory of Macropartisanship was further confirmed by Lebo, Walker, and Clarke (1998a) who estimate *d* to be equal to .82 with a standard error of .066. As a long-memoried series, the fluidity of partisan attachments suggested by MacKuen, Erikson, and Stimson is certainly over-stated.

Further, MacKuen, Erikson, and Stimson's macropartisanship equation regresses a fractionally integrated variable (d=.8) on two other fractionally integrated series with d=.91 (ICS) and d=.89 (presidential approval). They were thereby more likely than not to find significant relationships between their variables merely due to the troublesome presence of long-memory. Thus, for theoretical as well as empirical reasons, MacKuen, Erikson, and Stimson's failure to account for the long-memory of macropartisanship seriously compromises their findings.

To date, the most important departure from practices that encourage such threats to inference is made with Box-Steffensmeier and Smith's 1998 article, "Investigating Political Dynamics Using Fractional Integration Methods." The authors undertake a reappraisal of MacKuen, Erikson, and Stimson's macropartisanship specification by applying a fractional differencing filter.[4] Although their ARFIMA specification allows the equation to be estimated with a weakly stationary dependent variable, the authors leave their independent variables, presidential approval and consumer sentiment, in their original, fractionally integrated, form. But, as Chapter II demonstrated, the failure to deal with a fractionally integrated independent variable can cause problems on its own including the biasing downwards of standard errors and regression coefficients, and a slight rise in the probability of obtaining spurious results, i.e., an enhanced probability of type I errors.

Hence, while their explanation and treatment of macropartisanship as a fractionally integrated series is a significant improvement upon previous work, Box-Steffensmeier and Smith seem to have incorrectly constructed their multivariate ARFIMA transfer function. Perfecting the methods with which we analyze fractionally integrated data in multivariate models is a necessary step for researchers of political time series. With more confidence in the inferences derived from their models, researchers can gain a better understanding of complex political relationships such as those found in MacKuen, Erikson, and Stimson's "Macropartisanship" (1989).

The remainder of this chapter develops this methodology by testing a variety of ways of dealing with fractionally integrated data in multivariate models.

The Monte Carlo simulations of Chapter II demonstrate that fractional differencing on both sides of a bivariate model negates the threats to inference posed by the original long-memory of either variable. The remainder of this chapter extends this finding to the multivariate case. The several sets of simulation results below test the efficacy of fractional-, and unit-differencing as well as the option of leaving variables in level form. And, as was the case in Chapter II, the value of fractional differencing is again demonstrated.

3.2 Monte Carlo Simulations: Method and Control Simulation

For the most part, the multivariate simulations mimicked those of Chapter II. Specifically, RATS' ARFSIM procedure was used to randomly generate three series (Y_t, X_t, W_t) so that T = 150 and $d = 0.1$ for each series.[5] Next, depending on the simulation, some data transformation was performed on one, two, or all of the series. Then, using ordinary least squares (OLS), the dependent variable, Y, was regressed on a constant, and the independent variables X_t and W_t and the following output was recorded: X-coefficient estimates, X-standard errors, W-coefficient estimates, W-standard errors, R^2, and the Durbin-Watson statistic. This procedure was repeated 1,000 times. Next, the d value of X_t was increased by 0.1 and another 1,000 regressions were performed. After 10,000 regressions, the d value of W_t was increased by 0.1 and the procedure was repeated until 100,000 regressions had been performed. Finally, the value of Y_t was increased by 0.1 and the first three loops were repeated until a data set of 1,000,000 observations for each of the six statistics was created. For each regression the value of each of X's and W's t-statistic was calculated, and the number of times that the absolute value of t was greater than 1.96 was counted for each to determine the occurrence rate of type I errors at the .05 level of significance. As before, we should expect roughly 50 Type I errors for each set of 1,000 regressions.

To provide a basis for comparison, a control simulation was run. As in every simulation to follow, three series, Y_t, X_t, and W_t, were randomly generated from a (0,1) Beta distribution. However, for this experiment it was stipulated that each series would be mean, variance, and covariance stationary with d=0. For each of 100,000 regressions with Y_t as the dependent variable and X_t, and W_t as the independent variables, the X-coefficients, X standard errors, W-coefficients, W-standard errors, R^2, and Durbin-Watson statistic were recorded. The frequency of type I errors was calculated for each of the two independent variables and recorded as well. As before, the results of this control simulation conformed almost exactly with what we would expect based on probability and thus provide a reliable model for later comparisons.

The summary statistics for this multivariate control simulation are presented in Table 3.1. The coefficients for the independent variables X and W are normally distributed with a mean very close to zero (skewness= -0.001 and kurtosis = 3.001 for W; skewness = -0.021 and kurtosis = 3.035 for X) . The standard errors of X and W are normally distributed - though slightly skewed - with a mean of .0824 for each (skewness= 0.224 and kurtosis = 3.092 for W;

skewness = 0.255 and kurtosis = 3.112 for X). The Durbin-Watson statistic is normally distributed (skewness= -0.009 and kurtosis = 2.958) with a mean of 1.9993 indicating that on average there is no bias towards serial correlation in the error term. Although minuscule, the R^2 values average twice what they did for the bivariate control experiment, indicating the tendency of R^2 to rise with the addition of independent variables. Most importantly, at 5,286 and 5,189 for X and W, respectively, the occurrence rate of type I errors was statistically indistinguishable from the 5,000 we would expect at the .05 level of significance. A second control simulation estimated a first-order auto-regressive parameter in addition to the two stationary independent variables and found, as expected, this AR parameter to be significant roughly 5% of the time. Subsequent simulations demonstrate the need to use fractional differencing to avoid the threats to inference posed by fractionally integrated variables.

3.3 Multivariate Simulations: The Case of Under-Differencing

The simulations described below test a variety of methods for dealing with fractional dynamics on either side of a multivariate regression model. If the threats posed by non-stationary data are eliminated, regression results should follow those of the control simulation described above. The results indicate that, as is the case for bivariate regression investigated in Chapter II, threats to inference are minimized when all fractionally integrated variables are rendered d=0 through the process of fractional differencing. These results are described below after presenting the hypotheses of interest. The first of the three under-differencing hypotheses is:

$H_{3.1}$: In multivariate OLS regressions, fractionally differencing all variables by their respective estimated values of *d* produces spurious regression less often than does fractionally differencing only the dependent variable while leaving the independent variables in level form. This can be expressed as:

$H_{3.1}$: for $(1\text{-}B)^{d(Y)}Y_t = a + b_1(1\text{-}B)^{d(X)}X_t + b_2(1\text{-}B)^{d(W)}W_t + e_t$ AND

$(1\text{-}B)^{d(Y)}Y_t = a + b_3X_t + b_4W_t + e_t$

b_3 and b_4 will be statistically significant (.05) more frequently than either b_1 or b_2.

To confirm the value of fractionally differencing all variables, a second hypothesis was tested:

$H_{3.2}$: In multivariate OLS regressions, fractionally differencing all of the independent and dependent variables by their respective values of *d* will produce spurious regressions 5% of the time, i.e. at the same rate we would expect from stationary variables. This can be expressed as:

$H_{3.2}$: for $(1\text{-}B)^{d(Y)}Y_t = a + b_1(1\text{-}B)^{d(X)}X_t + b_2(1\text{-}B)^{d(W)}W_t + e_t$

each of b_1 and b_2 will be statistically significant (.05) 5% of the time.

As in Chapter II, the practice of fractionally differencing both sides is tested against the alternative of fractionally differencing the dependent variable and including a first-order autoregressive parameter as an independent variable along with two fractionally integrated independent variables left in level form. Hypothesis 3.3 speculates on the results of this comparison:

$H_{3.3}$: In multivariate regressions, fractionally differencing both the dependent and independent variables by their respective values of *d* produces spurious regressions less often than does fractionally differencing the dependent variable only and including a first-order autoregressive parameter as an independent variable along with untransformed fractionally integrated independent variables. This can be expressed as:

$H_{3.3}$: for $(1\text{-}B)^{d(Y)}Y_t = a + b_1(1\text{-}B)^{d(X)}X_t + b_2(1\text{-}B)^{d(W)}W_t + e_t$ AND

$$(1\text{-}B)^{d(Y)}Y_t = a + Y_{t-1} + b_3X_t + b_4W_t + e_t$$

b_3 and b_4 will be statistically significant more frequently than either b_1 or b_2.

To test these three hypotheses and to further investigate the consequences of various ARFIMA techniques, three sets of simulations were performed as described above. In Simulation 1, all of the variables were differenced by their assigned value of *d* prior to the regression. In Simulation 2, the dependent variable was fractionally differenced by its *d* value while the two dependent variables were left in level form. In Simulation 3, Simulation 2 was repeated with the addition of a lagged endogenous variable as an independent variable in the regression equation.

Simulation 1 Results

As per Hypothesis 3.2 and as is found in Chapter II, when both sides were fractionally differenced, the rate of spurious regressions was very near the perfect rate of 5%, with X and W being statistically significant 52,077 and 52,062 times out of 1,000,000 trials, respectively. Tables 3.2 and 3.3 show the rate of spurious regressions for X and W to be statistically distinguishable from 500 in

14 of Table 3.2's cells and in 10 of Table 3.3's cells.[6] While the rate of spurious regressions is slightly higher than it should be, with an overall rate of roughly 5.2 type I errors per 100, Hypothesis 2 is supported. Further, there is again no evident pattern to suggest that fractional differencing gains or loses its ability to prevent spurious regressions as *d* varies between 0 and 1.

A closer examination of the results of Simulation 1 reveals how fractionally differencing both sides of the equation guards against biases that would threaten inferences. The Durbin-Watson values of Tables 3.4 show no bias towards autocorrelation when each set of 10,000 regressions is averaged thus demonstrating the overall value of fractionally differencing both sides. A closer look at the coefficient estimates (Table 3.5) and standard errors (Table 3.6) of the independent variable, X, shows that these values do not change depending upon the variable's initial value of *d*.[7] Indeed, each of the sets of coefficients, standard errors, and Durbin-Watson statistics are normally distributed and have mean values nearly identical to those produced by the control simulation.[8] Comparing these results with those of Simulation 2 and Simulation 3, we see where problems arise when we fail to account for the fractional dynamics of the independent variables.

Simulation 2 & 3 Results

In Simulation 2, the independent variables were left in level form while the dependent variable was rendered *d*=0 by fractional differencing. As was seen in Chapter II, several problems emerged. Type I errors rose to 54,425 and 55,055 per 1,000,000 for the X and W variables, respectively. While this increase is not perilously high, it does represent an approximately 10% increase in spurious regressions and indicates that problems are likely present in the coefficient and standard error estimates. Tables 3.7 and 3.8 bear out this suspicion as one sees coefficients (shown in Table 3.7) and standard errors (shown in Table 3.8) biased downwards for an independent variable as its own value of *d* moves from 0 to 1.[9] Indeed, as *d* moves from .1 to 1.0, the average coefficient and standard error diminishes by roughly 75%.

The simultaneous downwards bias of coefficients and standard errors does guard against the inflation of t-statistics and type I errors but is nonetheless problematic. Without the ability to trust our estimates, coefficients lose their primary function as indicators of the size of the effect of one variable upon another. This is true not only for coefficients of standard independent variables but also for those of error correction mechanisms. The coefficient of an error correction mechanism specifies the rate at which cointegrating variables will return to equilibrium following a shock (Engle and Granger 1987; Banerjee, Dolado, Galbraith, and Hendry 1993). With bias in the estimation of this coefficient, our understanding of the equilibrium relationship will be misunderstood. Chapter IV shows how best to deal with error correction mechanisms in light of fractional dynamics. Hence, based on these problems, although Hypothesis 3.2 is not strongly supported, the consequences of leaving fractionally integrated independent variables in level-form are sufficiently troublesome to dismiss this method in favor of fractionally differencing both sides. Next, a lagged endogenous variable was added to verify that fractional differencing is the best method for dealing with fractionally integrated independent variables.

The results of Simulation 3 indicate that none of the problems found in Simulation 2 are alleviated by adding a lagged endogenous variable. The occurrence rate of spurious regressions for the two independent variables was 55,464 and 55,040 per 1,000,000 for W and X, respectively. This represents again the approximate 10% increase over what one should expect. Breaking down type-one errors for W by the *d* values of each of the independent variables, Table 3.9 shows the tendency of spuriousness to increase as *d* moves from 0 to 1. Note that in 65 of 100 cells in Table 3.9, the value is statistically distinguishable from the expected 500 type-one errors and that for the X variable the corresponding number is 64 out of 100. While not overwhelmingly high, these numbers are sufficient to support Hypothesis 3. Furthermore, the coefficients and standard errors for W shown in Tables 3.10 and 3.11, respectively, again show a downward bias as *d* increases.

Thus, a comparison of Simulations 1, 2, and 3 with the control simulation provides clear support for the option of fractionally differencing all variables by their respective values of *d*. Aside from supporting Hypotheses 1, 2, and 3, the problems evident in coefficient and standard error estimates also are serious enough to support the method of Simulation 1. Indeed, as seen in Chapter II, fractionally differencing all variables prior to their inclusion in a regression yields results identical an all respects to those obtained in a regression where *d*=0 for all variables initially. Next, the option of fractionally differencing independent variables is compared with the option of wholly differencing them.

3.4 Multivariate Simulations: The Case of Over-Differencing

Although simulations 2 and 3 tested the consequences of assuming no long-term memory in the independent variables, the following two simulations test the consequences of assuming perfect memory, first in the independent variables, and, second, in all the variables. As discussed in Chapter II, over-differencing a variable will introduce negative auto-correlation into its error term and threaten inferences made using bivariate or multivariate regression models. For the case where a dependent variable is over-differenced only to a slight extent, these threats may remain low and the autocorrelation can be accommodated by including a moving average process. However, as the degree of over-differencing increases autocorrelation can wreak havoc on estimates and often, by creating non-invertible moving average processes, make estimation impossible. Although Chapter II establishes most of these practical difficulties, two additional simulations are presented here to demonstrate the continuing usefulness of fractional differencing when one moves from the bivariate to the multivariate case.

Simulation 4 & 5 Results

Simulation 4 regresses a fractionally differenced dependent variable on a constant and two wholly differenced variables, thus testing the consequences of over-differencing only on the right-hand side of a regression model. While this approach is one unlikely to be chosen purposely, we can envision the case where Dickey-Fuller tests suggest to a researcher that his/her dependent variable is stationary but that their independent variables requires differencing to achieve stationarity. The results of Simulation 4 suggest that the negative effects of this approach are relatively mild but nonetheless significant. With 51,518 and 51,681 type I errors for W and X, respectively, spurious regressions were not a problem. Further, over-differencing the independent variables produced only the slightest positive autocorrelation as evident in the Durbin-Watson values of Table 3.12. However, this tendency was minuscule even where X and W had each been drastically over-differenced.

Once again, the true problem of this approach was found to be a simultaneous biasing downwards of coefficients (Table 3.13) and standard errors (Table 3.14). Although not as strong as that seen in the under-differencing simulations, the bias downwards of roughly 25% in cases of drastic over-differencing is sufficient to warn against this practice. Again, the failure of t-statistics to rise is the result of two wrongs - downward bias in both standard errors and coefficients - making a right.

Simulation 5 tested the more relevant case of over-differencing both the dependent and independent variables. Given the commonality of fractional integration (Lebo, Walker, and Clarke 1998a) and given many researchers' reliance upon stationarity tests incapable of distinguishing between unit-root and fractionally integrated processes, over-differencing both sides of a regression is a common mistake. The results of this simulation show that the consequences of this mistake are significant. The occurrence rate of Type I errors for W and X were 71,080 and 70,900 per million, respectively, indicating roughly a 40% loss of efficiency in the 5% probability level. Table 3.15 demonstrates that as the degree to which an independent variable has been over-differenced increases, so too does the likelihood of finding a statistically significant relationship between it and a dependent variable. Isolating the case where the *d* value of Y equals a value common for a political variable, 0.7, Table 3.16 shows that even where over-differencing of the dependent variable is slight (0.3), significant relationships become far more frequent than chance should allow. As before, spurious regressions increase as standard errors are biased downwards faster than are coefficient estimates. One final problem arises from over-differencing both sides of the equation. As found earlier, negative autocorrelation continues to plague these regressions with Durbin-Watson statistics averaging 2.533 (Table 3.17). Note that this autocorrelation appears uniform throughout Table 3.17 because it is dependent wholly on the over-differencing of Y.

3.5 Conclusion

From the Monte Carlo experiments presented here, it is clear that fractional differencing maintains its utility in multivariate models. Complex models of political relationships should begin by estimating values of *d* for each variable and then should difference each variable by its own value of *d*. In so doing, researchers avoid introducing autocorrelation into their analyses, avoid biasing their coefficients estimates and standard errors, and minimize the possibility of finding a significant relationship between two variables where none truly exists. Furthermore, avoiding the knife-edged decision between stationarity (I(0)) and unit-root behavior (1(1)) will allow competing researchers to come to a consensus as they first agree on the time series properties of their variables and then move on to investigate the relationships among them. In the following two chapters, complex multivariate ARFIMA models of political relationships are developed and used to demonstrate the value of rendering variables d=0. Chapter IV considers models of governing party support in Great Britain and Chapter V studies the determinants of presidential approval in the United States.

Endnotes

1. Using Robinson's (1995) Gaussian Semi-Parametric Estimator. Sowell's (1992) exact maximum likelihood estimator was also used and yielded *d* estimates and standard errors of 0.928 and .085 for presidential approval and 0.874 and .070 for the ICS. Robinson's estimation procedure (RGSER.SRC) is available for RATS on the Estima web page: http://www.estima.com. Values are derived from the estimation of (0,1+*d*,0) models. The variables are first-differenced before estimation because of the constrained parameter space that does not allow estimation of the long memory parameter except when $-1.5 < d < .5$ (see Hamilton 1994: 449). Sowell's estimator is available as part of OX, the matrix language that accompanies PCGive 9.0 and is also available on its own on the web at: http://www.nuff.ox.ac.uk/Users/Doornik (June, 1999). Again, data must be first differenced before estimation. As the output of each of Sowell's and Robinson's procedures reflects an estimate of *d* for the first differenced series, 1 must be added to these estimates to obtain the *d* value of the original series. See Baillie (1996) for a more complete explanation of these estimation procedures. Chapter IV discusses methods of estimating *d* in greater detail.

2. Box-Steffensmeier and Smith (1998) estimated *d* values for the ICS and presidential approval to be .258 and .261, respectively with standard errors of .329 and .297. They were thus unable to reject the null hypothesis of weak stationarity for either variable. These *d* values are extremely suspect, however, as they were estimated simultaneously with autoregressive and moving-average parameters in (3,*d*,3) models. Box-Steffensmeier and Smith use these more complex models based upon the suggestions of OX's incorrectly calculated Schwartz Information Criterion which failed to properly discriminate against less parsimonious models. Using the Akaike Information Criteria (AIC), Lebo, Walker, and Clarke (1998a) find the ICS is best characterized by a (0,*d*,0) process and that presidential approval is best characterized by a (1,*d*,0) process (see Akaike 1973, 1974; and Chatfield 1996: 226 for a complete discussion of the AIC).

3. Rejection of the unit-root hypothesis at the .05 level of significance was not possible for the ICS with t=1.32 but was just possible for presidential approval with t=1.66.

4. For another conception of how to understand macropartisanship see Green, Palmquist, and Schickler's *APSR* article "Macropartisanship: A Replication and Critique." In their response to Green, et al., Erikson, MacKuen, and Stimson maintain that they are still unconvinced that macropartisanship is anything other than a stationary AR1 process (Erikson, MacKuen, and Stimson, 1998). Finally, Walker and Lebo (1999 working paper) re-conceive the macropartisanship equation by fractionally differencing each of macropartisanship, presidential

approval, and the index of consumer sentiment.

5. As was done for the bivariate simulations, values for the simulated series were drawn from a (0,1) Beta distribution. See Appendix 2 for RATS programs and seed values.

6. Again, each cell should be conceived of as a sample observation of an entire population of t-statistics. The overall population is normally distributed and one in 20 individuals have an absolute value greater than 1.96. To judge whether any observation is statistically distinguishable from the expected value of 500 per 10,000, a confidence interval is used as follows:

$\Pi = P \pm 1.96\,[(P(1-P))/n]^{1/2}$ where P = .05
simplified... $\Pi = .05 \pm .00427$

Thus, 95% of the observations should fall between 457.3 and 542.7 (see Wonnacott and Wonnacott, 1990; 273). Note that this confidence interval is not simply ten times that of the confidence interval in Chapter II. The consistency of the OLS regression results is apparent as the distribution becomes steeper with an increased sample size. (For a detailed description of the Central Limit Theorem see Kmenta 1986 or Bohrnstedt and Knoke 1988).

7. The values in these tables are nearly identical to those of the second independent variable, W.

8. For the W coefficient, skewness = -0.001 and kurtosis = 3.035. For the X coefficient, skewness = 0.006 and kurtosis = 3.034. For the W standard error, skewness = .230 and kurtosis = 3.124. For the X standard error, skewness = .223 and kurtosis = 3.101. For the Durbin-Watson statistic, skewness = 0.000 and kurtosis = 2.958. Skewness scores should be as near to 0 as possible and kurtosis scores should be as near to 3 as possible (Hamilton 1993). Note that the slight skewness in the distribution of the standard errors is the same as was seen in the control simulation.

9. Further, Tables 3.7 and 3.8 demonstrate the tendency for one independent variable's standard error and coefficient estimate to rise slightly as the *d* value of another independent variable rises. This is likely due to increases in multicollinearity between the two independent variables as *d* increases for both.

CHAPTER IV

FRACTIONAL COINTEGRATION AND MODELS OF GOVERNING PARTY SUPPORT IN GREAT BRITAIN

4.1 Introduction

Based on the Monte Carlo results of Chapters II and III, it is apparent that multivariate models of political relationships need to account for the fractional dynamics of their variables. Through the process of fractional differencing variables can be rendered d=0 and thereafter included in multivariate models without threatening inferences. This chapter seeks to apply these findings while investigating the question of what drives governing party support in Great Britain. Also, following Cheung and Lai (1993), the problem of fractional dynamics is extended to the methodology of cointegration and error correction mechanisms in models of British politics.

The chapter begins by reviewing the debate regarding various specifications of governing party support in Britain. This is followed by arguments concerning why one should expect the British variables of governing party support, prime ministerial approval, and four subjective measures of economic performance each to be fractionally integrated. Tests of stationarity are discussed and applied to the British data as are methods for estimating the fractional differencing parameter, *d*.

A discussion of the relatively new concept of fractional cointegration follows and the plausibility of fractionally-integrated error correction mechanisms is considered. Next, tests of fractional cointegration between the variables are presented. Governing party support is then explained in terms of a multivariate ARFIMA model that includes a fractionally-differenced error correction mechanism. Finally, encompassing tests are employed to address first the controversy concerning what kind of economic evaluations drive governing party support in Britain and, second, the topic regarding how model specification can be improved through the use of fractional integration and fractional cointegration techniques.

4.2 Prospections, Retrospections and Prime Ministerial Approval

As the link between objective economic conditions and individuals' perceptions of their own and their country's financial well-being, survey data collected by in Britain by Gallup have proven useful in terms of predicting governing party support (Sanders 1991; Sanders 1995; Clarke and Stewart 1995; Clarke, Stewart, and Whiteley 1997). Indeed, the compilation of several long series of subjective economic evaluations has greatly enhanced the ability of researchers to isolate the most important economic factors that affect voting decisions. Although a consensus has grown regarding their advantages, debate continues about which subjective measure is most valuable as a predictor of party support.

On the one hand, Key's (1966) claim that voters punish or reward incumbents for the state of their pocketbooks strongly supports retrospective evaluations (hereafter the PR model). In contrast, Sanders' use of personal expectations (hereafter the PE model) was a key to his impressive ability to predict the surprise Conservative victory in the 1992 British General Election (Sanders 1991).

Further, debate exists between those such as Key and Sanders who emphasize the importance of personal, or 'egocentric,' evaluations and others such as Kinder and Kiewiet (1981) and MacKuen, Erikson, and Stimson (1992) who favor national, or 'sociotropic,' evaluations. MacKuen *et al.* (1992) argue convincingly that national expectations (hereafter the NE model) outperform the national retrospection (NR) model for the case of American presidential approval while Kinder and Kiewiet (1981) and many others (see Clarke et. al., 1992: Ch. 1) favor national retrospections.

Despite the controversy between the advocates of these competing models, it should be noted that the variables at issue are quite similar. Clarke and Stewart (1995) observe strong correlations among the four subjective measures (averaging r=.67 from 1979-1992) and between each of the four measures and governing party support but nevertheless find personal measures to be preferable to national ones. That these authors find no clear winner between Key's PR model and Sanders' PE model suggests that perhaps the longer period of data and the more sophisticated methodological approach provided herein may be useful in clearing up the question of which model works best.

An additional controversy among analysts of the dynamics of party support in Britain concerns the inclusion of prime ministerial approval as an explanatory variable (see, e.g., Butler and Stokes 1976; Clarke, Ho, and Stewart 1998). The close relationship between the two variables (r=.91 for 1979-1996) is sufficient to make one wary of including prime ministerial approval as an independent variable (Clarke, Ho, and Stewart 1998). Indeed, if the variables are too closely related, modeling one in terms of the other is paramount to modeling one in terms of itself, a pointless exercise. Yet, as the embodiment of the party in power, it is important to include support levels for the prime minister in any attempt to predict support for the party in power (Crewe and King 1994; Clarke and Stewart 1995).

These latter theoretical and methodological controversies have motivated the use of sophisticated techniques such as tests for cointegration and the development of models that include error correction mechanisms to capture the long-run equilibrium relationship between variables (Clarke and Stewart 1995; Clarke, Stewart and Whiteley 1997; Clarke, Ho, and Stewart 1998). Later, it is shown that the assumptions of cointegration are too restrictive and that the relationship between prime ministerial approval and governing party support is best described as fractionally cointegrated. First, however, I present a brief discussion of how fractional dynamics arise and, second, why one should expect the British data to exhibit this property.

4.3 Fractional Dynamics and the British Case

Granger (1980) explains three ways by which a fractionally integrated series can be created. In the first case, aggregating individual-level heterogenous behavior will produce fractional dynamics. This heterogeneity exists with respect to various autoregressive and moving average tendencies (see equation (1.2)). The aggregated series will long remember the behavior of individuals with strong auto-regressive tendencies while quickly forgetting the behavior of others. Eventually, the series will revert to a long-term mean, but this may not occur until some time in the distant future. Fractional dynamics also may arise, Granger (1980) explains, when we aggregate data with dynamic relationships at the individual-level or when the disturbance term of a series is fractionally integrated. Of these three possibilities, it is the first that is relevant here.

Indeed, governing party support, prime ministerial approval, and the four subjective evaluations of the economy are each constructed by aggregating the opinions of a random sample of individuals. While Granger's forewarning should immediately alert us to the possibility of fractional integration, theoretical debate among partisanship scholars gives rise to this suspicion as well. On the one hand, Green and Palmquist (1990, 872) state that "the outstanding characteristic (of party identification) is persistence over time." Realignment theories also assume a great deal of persistence over time that can only be interrupted by major shocks (Burnham 1970; Clubb, Flanigan, and Zingale 1980; Sundquist 1983; Box-Steffensmeier and Smith 1996).

On the other hand, Converse's (1964) Black/White model and Key's (1966) Switchers/Stand-patters model both suggest that partisanship is immovable for some citizens while for others minor disturbances can cause them to shift allegiances. In their examination of the British electorate, Byers and Peel (1997) argue that understanding that the electorate is composed of "committed" and "uncommitted" voters necessarily leads to the conclusion that approval measures will be fractionally integrated. The stronger partisan attachments of the committed voters will dictate their opinions and their votes while the uncommitted will base these decisions on short-term factors such as performance (Box-Steffensmeier and Tomlinson 1999).

Hence, it becomes easier to imagine volatility when we move from partisanship to survey responses measuring voting intentions, leadership approval, and subjective evaluations of the economy. Allsop and Weisberg (1988) show that voting intentions can oscillate over short periods while actual partisanship remains relatively stable. In the American case, the popularity of split ticket voting is further evidence that, even if partisanship is persistent, individuals' voting behavior - and their voting intentions as measured in surveys - are considerably more erratic (Fiorina 1990). Thus, the size of a shock needed to induce some to switch their vote intention is smaller than that needed to alter their partisanship. Smaller still is the size of a shock needed for some respondents to alter their responses on political questionaires. For the less politically sophisicated, the size of this shock may be such that their expressed opinions may be based upon the party foremost in their minds at the time they are surveyed (Taylor and Fiske 1978; Zaller 1992).

Zaller (1992) hypothesizes that political knowledge is distributed normally with individuals with high and low levels of information at the extremes. For persons with a great deal of political knowledge it will take a tremendous amount of new information to sway their opinions. However, those in the middle of this distribution are susceptible to recent information and will incorporate it into their assessments and their opinions. Lastly, the responses of those with low levels of information may change based upon the slightest of shocks such as a newspaper headline or a six o'clock news sound-bite.

Thus, within each monthly sample of the British data there will be individuals with a diverse array of auto-regressive tendencies, the distribution of which will determine the degree of persistence in an aggregated series. One may speculate that some variables, such as prime ministerial approval, are likely to be dominated by stayers/stand-patters as most people's opinions of the country's leader are unlikely to change from month to month. On the other hand, subjective economic evaluations are far more likely to be volatile at the individual level as people continually reassess personal and national fortunes in light of updated information about national and personal economic conditions.[1]

Hence, there are several reasons to suspect that fractional dynamics will characterize the series of interest. Previous chapters demonstrate that failing to fractionally difference fractionally integrated independent variables leads to a host of problems including the downward bias of Durbin-Watson values and the upward bias of standard errors and, subsequently, spurious regressions. Thus, to avoid the problems presented by under-differencing as well as those of over-differencing, one should take two preliminary steps prior to developing multivariate models. First, the nature of memory, *d*, should be identified for each variable and, second, in order to render error terms white-noise processes, each variable should be differenced by its own value of *d*. Following a discussion of the data, tests of stationarity and estimates of *d* are employed to accomplish the first of these tasks.

4.4 Data, Tests of Stationarity, and Point Estimates of *d*

As did the first Thatcher government, the monthly British data used herein begin in August, 1979. The six series end in December, 1996, four months before the Conservatives' defeat in the May 1, 1997 general election.[2] Hence, the British case provides one with the rare opportunity to study over two hundred months of single party rule in a mature democracy. The first Gallup variable is governing (Conservative) party support, calculated by adding the percentage of respondents replying "Conservative" to the question "If there were a general election tomorrow, which party would you support?" to the percentage who replied "don't know" to the latter question and "Conservative" to the subsequent question: "Which party would you be most inclined to vote for?" The second variable, prime ministerial approval, was calculated as the percentage saying they are "satisfied" to the question, "Are you satisfied with [name] as prime minister?" The remaining four variables are subjective economic evaluations calculated by subtracting the percentage of negative responses from the percentage of positive ones to the following questions:

(a) personal expectations (or prospections) - “How do you think the financial situation of your household will change over the next 12 months?”

(b) personal retrospections - “How does the financial situation of your household now compare with what it was 12 months ago?”

(c) national expectations (or prospections) - “How do you think the general economic situation in this country will develop over the next 12 months?”

(d) national retrospections - “How do you think the general economic situation in this country has changed over the last 12 months?”

Each variable is bounded between -100 and +100 and is an aggregate measure of individual-level behavior, characteristics that both suggest fractional integration (Granger 1980; DeBoef and Granato 1997b). Multiple tests of stationarity and estimation of *d* for each show the hypothesis of fractional integration is suggested by the data.

While several tests of stationarity exist, each is limited in its own way (Maddala and Kim 1998). Thus, it is a sound idea to rely upon multiple tests of stationarity in addition to point estimates of *d* to ascertain a series’ degree of integration.[3] Four such tests, each of which addresses the problem of stationarity in a different way, were used. The first of these tests was the Dickey-Fuller test (Dickey and Fuller 1979, 1981).

The Dickey-Fuller unit-root test uses the following regression model:

$$\Delta\psi_\tau = \alpha_{0\,+}\,\gamma\psi_{\tau\text{-}1} + \alpha_2\tau + \Sigma\,\Delta\psi_{\tau\text{-}\pi} + \epsilon_\tau \tag{4.1}$$

In its basic form, the Dickey-Fuller equation includes a differenced version of the series of interest, lagged values of the level-form series, and the error term. Testing for a random walk with drift requires the addition of the constant term, α_0. Testing for a deterministic time trend adds $\alpha_2\tau$. The null hypothesis for the test is a unit-root with or without drift, γ=0, against the alternative hypothesis that γ<0. To deal with autocorrelation in the error term, the augmented Dickey-Fuller test (ADF) inserts lagged values of $\Delta\psi_\tau$ so that the Dickey-Fuller regression residuals are rendered white noise and inferences about γ become possible.

Table 4.1 shows the results of the Dickey-Fuller tests for the British data. While each of the four subjective economic measures rejects the null hypothesis of a random walk at the .05 level, Conservative party support and prime ministerial approval look to be borderline cases in the *d*=0 vs. *d*=1 dichotomy. However, these results are suspect given findings that the Dickey-Fuller test has low power in light of fractional alternatives (Diebold and Rudebusch 1991). With the likelihood of fractional processes, it is preferable to use a test with an alternative hypothesis of fractional behavior. The variance ratio test is appropriate for this purpose.

The variance ratio test is useful because it tests a null hypothesis of a random walk with drift against an alternative hypothesis of pure fractional noise

($(1-L)^d x_t = e_t$) (Diebold 1989).[4] Given that a unit-root series will never forget a random shock, the variance ratio test tests the hypothesis that the variance in period k should be k times the variance in period 1. The test statistic, R(k), is formally given in (4.2) with k as the differencing interval.

$$R(k) = \frac{k\hat{\sigma}_1^2}{\hat{\sigma}_k^2}, k = 2,3,\ldots,K., \ \ where \tag{4.2}$$

$$\hat{\sigma}_k^2 = \frac{1}{(T-k+1)}\sum_{t=k}^{T}(x_t - x_{t-k} - k\hat{\mu})^2, \ for\, k = 1,2,\ldots,K;$$

$$and \ \ \hat{\mu} = \frac{1}{T}\sum_{t=1}^{T}(x_t - x_{t-1})$$

The results of the variance ratio tests shown in Table 4.2 are generally similar to the Dickey-Fuller results. The null hypothesis of random walk with drift is rejected (.05) for each of the four subjective economic measures as well as for Conservative party vote intentions. Again, the null hypothesis of a random walk cannot be rejected for prime ministerial approval. Some discrepancies do exist between the results of the Dickey-Fuller tests and those of the Variance Ratio tests, however. Although each set of results indicate that unit-root behavior does not characterize the four subjective measures, the differences between the tests' alternate hypotheses determine that the tests are unable to agree on whether d=0 or 0<d<1. It is therefore useful to employ additional tests that test a null hypothesis of stationary behavior against fractional alternatives. The tests developed by Kwiatkowski, Phillips, Schmidt, and Shin (1992, KPSS hereafter) fit this description, and thus allow further clarification of the dynamics of the British series.

The KPSS tests (1992) focus on two distinct processes in the series under examination. The tests separate the series into a deterministic trend, a random walk, and a stationary error term (KPSS 1992: 162). The series is then tested for strong mixing properties using a score test shown in (4.3). Strong mixing refers to the tendency of a series' autocorrelation function to die down quickly as correlations between time points are "mixed" away at a constant, exponential rate (KPSS 1992).

$$\eta_\mu = T^{-2}\sum_{t=1}^{T}\frac{S^2}{s^2(l)} \qquad where \qquad S_t = \sum_{i=1}^{t}\varepsilon_i \tag{4.3}$$

In (4.3), T represents the sample size, $s^2(l)$ is an estimate of the disturbance variance, and S_t is the partial sum of the residuals, e_i. The first of the two KPSS tests, η_μ, employs a base equation consisting solely of the stationary errors and an intercept parameter to test for strong mixing against an alternative of either a unit-root or fractionally integrated process. The second test, η_τ, adds a linear trend to the intercept and errors and tests the same null and alterative hypotheses. Lee and Schmidt (1996) demonstrated the ability of the KPSS tests to be consistent against I(*d*) alternatives and thereby found them useful in distinguishing among short- and long-term dynamics. Political scientists have also begun to appreciate the usefulness of the KPSS tests (Ostrom and Smith 1993; Box-Steffensmeier and Smith 1996, 1998).

Table 4.3 shows the results of the first KPSS test, η_μ. Looking at column 3 with the recommended lag truncation parameter of 4, we see that Conservative party support and prime ministerial approval each reject the null hypothesis of strong mixing at the .01 level. The egocentric economic measures reject the null hypothesis only at the .10 level and neither of the sociotropic measures is capable of rejecting the hypothesis that d=0.

Table 4.4 shows the results of the second KPSS test, η_τ. Here the results are nearly unanimous as all but national expectations fail to reject the null hypothesis of strong mixing at the .01 level. Thus, trend stationary processes do not describe these series. Combining the results of these KPSS tests with those of the variance ratio tests and the Dickey-Fuller tests, it is evident that the stationary/integrated (I(1)) dichotomy is too restrictive for these series.

Table 4.5 summarizes the results of all the stationarity tests. Based solely on these tests, it seems that Conservative party support and prime ministerial approval are each characterized by a greater degree of persistence than are any of the subjective economic measures. Indeed, no test rejects the possibility that prime ministerial approval is a unit-root series. Nevertheless, while these tests are helpful for preliminary diagnoses of time series, generating direct estimates of the order of integration remains an important next step.

The exact value of d may be estimated using several techniques including semiparametric estimation (Geweke and Porter-Hudak 1983; Robinson 1995), approximate maximum likelihood estimation in the frequency domain (Fox and Taqqu 1986), and exact maximum likelihood estimation in the time domain (Sowell 1992).[5] Before looking at the results of two of these procedures, the advantages and disadvantages of each are discussed.

Sowell (1992) finds that the approximate maximum likelihood techniques of Fox and Taqqu (1986) and the semiparametric estimation techniques of Geweke et al. (1983, GPH hereafter) each have undesirable properties when sample size is small. Given the relatively short length of most political time-series, this is particularly unfortunate. Hurvich and Ray (1995) find the semiparametric estimation of GPH to be less than optimal as bias exists in estimates of d and mean square error.[6] Though it has yet to be thoroughly examined, Robinson's (1995) gaussian semiparametric estimation technique, available in RATS, seems to be a significant improvement upon the GPH estimator. Sowell's (1992) full maximum likelihood estimation, available in OX, has also proven to be a reliable and easy to implement method of estimating d.[7] Yet in their survey of these rival procedures, Smith, Sowell, and Zin (1993, 1996) conclude that there are small bias tradeoffs using either approximate maximum likelihood or Sowell's estimation procedure. Based on these studies, it seems that Robinson's procedure is most appropriate with Sowell's the best alternate.[8]

Thus, the d value for each of the British series was estimated using both Robinson's and Sowell's estimator. Searching for the best noise model that accounted for both the short- and long-term dynamics of each series, d was estimated for each variable in a $(0,d,0)$ model and in (p,d,q) models containing up to three autoregressive and three moving average parameters. The Akaike Information Criterion (Akaike 1973, 1974), and the Schwartz Bayesian Criterion (Enders 1995) were employed to distinguish which of the 16 models per variable was superior.[9] According to the BIC, the (0,*d*,0) model was the best noise model for each of the six variables. According to the AIC, the (0,*d*,0) models also work best for each variable.[10]

Table 4.6 shows the results of the *d* estimates using both Robinson's semiparametric estimator and Sowell's full maximum likelihood estimator. It is immediately apparent that the two procedures yield very similar estimates. Indeed, in all but one case, the estimates are within one standard error of one another. Furthermore, the two estimators strongly agree that *d* does not equal zero for any of these series and that *d* does not equal one for every series save prime ministerial satisfaction. While estimates for *d* of .96 and .91 for this variable indicate fractional integration, they are each within two standard errors of one and thus rejection of the unit-root hypothesis is impossible. Based on these results, we can conclude that fractional integration characterizes five (and perhaps all) of the six series. Next, the concept of fractional cointegration is discussed and used to analyze the relationship between Conservative vote intentions and prime ministerial approval.

4.5 Fractional Cointegration and Fractional Error Correction Models

Just as the likelihood of finding fractional dynamics in political variables motivates a reconfiguration of standard regression techniques, the methodology of cointegration must likewise be rethought in light of the possibilities of long-memoried equilibrium relationships between variables. Among the advantages of this new methodology is the ability to identify more precisely the equilibrium relationship between two or more variables. Thus, along with ARFIMA modeling, fractional cointegration techniques improve the chances for rival modelers to reach a consensus on the nature of the relationships among their variables. The concept of fractional cointegration is most easily explained as a more general form of traditional cointegration.

Cointegration can be understood as a long-term relationship between two or more variables (Granger 1981; Engle and Granger 1991; Beck 1993). An equilibrium relationship exists between the variables so that shocks to one variable are gradually "re-equilibrated" and the long-term relationship continues (Clarke, Stewart, and Whiteley 1997; Box-Steffensmeier and Tomlinson 1999). Standard operating procedure for finding cointegration relies on, first, finding each of the original series to be unit-roots (I(1)) and, second, finding the residuals of a cointegrating regression to be white-noise (I(0)). Simple unit-root tests such as Dickey-Fuller are a usual method for assessing the order of integration (Dickey and Fuller 1979).[11] However, when one ceases to demand that *d* has an integer value and one realizes the infinite values on the number line between 0 and 1, it is evident that one's chances to find potential candidates for cointegration are drastically reduced (Barkoulas and Baum 1997; Dueker and Startz 1998). In terms of the first step, finding unit-roots is a difficult task, especially when using aggregate measures of survey data (Lebo, Walker and Clarke 1998a). Also, the hope of finding residuals to be I(0) seems unnecessary as it should be enough to find that these equilibrium errors are mean reverting (Cheung and Lai 1993). The key point is that despite being fractionally integrated and thereby demonstrating persistence in the short-run, as long as the equilibrium errors are mean reverting in the long-run and are of a lower order of integration than are either of the initial variables, the initial variables are in equilibrium and can be said to cointegrate.[12]

Hence, relaxing these assumptions of integer-level integration seems a viable way of fusing the methodology of cointegration with the concept of fractional integration (Cheung and Lai 1993; Dueker and Startz 1998). Abadir and Taylor (1998, p. 6) redefine a bivariate cointegrating relationship as follows: two variables, $\{Z_t\}$ and $\{X_t\}$ where $Z_t \sim \mathrm{I}(d)$ and $X_t \sim \mathrm{I}(b)$ are cointegrated if $\exists g(.)$ such that $\eta_t \equiv Z_t + g(X_t) \sim \mathrm{I}(s)$ and $s < d$.[13]

Thus, each of the parent and residual series may be I(d) where $d \in [0,1]$ and the existence of some function $g(X_t)$ that reduces the order of integration for Z_t establishes that Z_t and X_t are cointegrated (Abadir and Taylor 1998; Box-Steffensmeier and Tomlinson 1998). As will be shown, such a relationship exists between Conservative party support and prime ministerial approval.

Next, with the extension of the methodology of cointegration to include cases of fractional cointegration, it is likewise reasonable to update the methodology of error correction mechanisms (ECMs). Standard practice is to employ an error correction mechanism when two series cointegrate in the traditional sense (Engle and Granger 1987). The use of the ECM allows the specification of both short- and long-term relationships among two or more non-stationary variables (Clarke and Stewart 1995; Charemza and Deadman 1997). Among the assumptions of the ECM methodology is that the residuals of the cointegrating regression, and hence, the ECM, are I(0). Relaxing this assumption to allow for the possibility of fractional cointegration is a natural extension of standard cointegration methodology. Indeed, the Granger Representation Theorem only requires a cointegration vector to be stationary making it wholly unnecessary to expect the ECM to be an I(0) process (Granger 1981, 1983; Baillie and Bollerslev 1994). Rather than using Dickey-Fuller unit-root tests to make the "knife-edge" decision between I(0) and I(1), point estimates of the *d* parameter for the ECM allow a more complex understanding of the nature of the equilibrium relationship. Thus, the range of possible behavior for the ECM is greatly increased. Defining an ECM as possessing long memory simply implies that shocks to one variable are re-equilibrated at a slower rate than the normal exponential decay of an ARMA process.[14]

The existence of a fractionally integrated ECM does present a problem to the multivariate modeler, however. If one wishes to include a fractionally integrated ECM as an independent variable in a larger equation, one should be wary of the threats to inference generated by its long-memory characteristics. As found in Chapter III, even in the presence of a dependent and other independent variables for which I=0, a single fractionally integrated independent variable will threaten inferences. Specifically, coefficient estimates and standard errors are biased down drastically and the rate of spurious results increases slightly. Thus, our interpretation of an ECM's coefficient as a measure of the strength of the adjustment mechanism will be severely flawed.

Hence, it is important to remember the standard admonition and ensure that ECMs are I(0) before including them in multivariate equations. As shown below for the case of British governing party support, this can be done simply by fractionally differencing the residuals of the cointegrating regression by their estimated value of *d*. This process necessarily entails avoiding one-step ECM procedures such as those of Johansen (1988) and Stock and Watson (1988) in favor of the traditional two-step approach of Engle and Granger (1987).[15] A full multivariate ARFIMA model with an ECM specification can thereby be estimated without worrying about threats to inference posed by any fractionally integrated component. Prior to demonstrating such a model, prime ministerial approval and Conservative party support are tested for fractional cointegration.

Previous studies of the relationship between public support for political parties and their leaders have been correct both in their speculation that some long-run equilibrium relationship exists between the two variables and in their use of error correction mechanisms to guard against under-differencing non-stationary variables (Beck 1992; Clarke and Stewart 1994; Clarke and Stewart 1995; Smith 1993; Clarke, Ho, and Stewart 1998). Indeed, Figure 4.1 shows the close relationship between governing party support and prime ministerial approval. However, in light of the possibilities of fractional cointegration, it is possible that previous research has over-estimated the rate at which leader support and party support will return to equilibrium following a shock.

To test for this possibility with the British data, a cointegrating regression was performed between prime ministerial approval and Conservative party vote intentions and the residuals (the error correction term) were tested for stationarity. The *d* estimate for the ECM was .59 (s.e.=.059), over 4 standard errors below the *d* values for either of the initial variables indicating the presence of fractional cointegration.[16] Figure 4.2, a graph of the autocorrelations of the ECM, demonstrates the slow decline that is the signature characteristic of long-memory (Lo 1991; Baillie and Bollerslev 1994). The presence of mean-reverting long-memory in the ECM tells us that a shock to one variable will persist longer than a geometric decay would suggest but that this shock will dissipate as the variables eventually return to equilibrium. Hence, conclusions of a cointegrating (d=0) relationship between prime ministerial approval and conservative party support (such as found in Clarke and Stewart, 1995) over-estimate the speed with which the two variables return to their long-term equilibrium following a shock to one of the variables. Next, it will be shown how accounting for this long-run relationship in more complex multivariate models improves model specification.

4.6 Multivariate Models of Conservative Party Support

I now consider multivariate models of Conservative party vote intentions. To ensure that threats to inference were minimized, Conservative party support, prime ministerial approval, and the four subjective measures were rendered d=0 by fractionally differencing each by its own value of d (see Table 4.6 for these values).[17] Figure 4.3 shows the similarity between governing party support in differenced and fractionally differenced form. As will be shown, the differences between these two series are nevertheless significant for multivariate analyses. In order to account for the long-term equilibrium relationship between Conservative party support and prime ministerial approval, the error correction term (lagged back one period) is included in the multivariate models. Before its inclusion, however, the ECM was fractionally differenced by its d estimate, .59. Note that the desire to include only d=0 variables in the multivariate models led to the use of a 2-step ECM procedure.[18]

The models also include as independent variables interventions for the national elections of 1983 and 1992, the Falklands war, the introduction of the Poll Tax, and the beginning of John Major's tenure as prime minister and leader of the Tories. Finally, an additional variable, EVENTS, is used to capture shifts in public opinion likely to result from various miscellaneous political and economic events.

Conservative party support was used as the dependent variable in the four separate analyses shown in Table 4.7. Column 1 of Table 4.7 shows personal expectations to be significant (.05 level) along with prime ministerial approval, the error correction mechanism, and each of the intervention variables. Column 2 shows a nearly identical pattern with personal retrospections being significant. However, turning to columns 3 and 4, we see that evaluations of personal finances outperform the national measures. Indeed when other factors are controlled, both of national expectations and national retrospections fail to achieve statistical significance in their respective models, thus supporting the “egocentric” thesis.

Between the two personal variables, personal retrospections appears to be a slightly better predictor of conservative support than are personal expectations. Encompassing tests (j-test, see Mizon 1984; Mizon and Richard 1986) between the two show that neither model encompasses the other (see Table 4.9). To check this latter result, each of the PR and PE models was run using the one-step procedure and encompassing tests followed (see Table 4.10). Again, neither model encompassed the other. Thus, the inclusion of new data and the use of fractional techniques is insufficient to decide between these two highly correlated variables as to which one is a better predictor of governing party support in Britain.

I was also interested in testing the efficacy of my multivariate ARFIMA modeling approach. Several rival methods were tested for the personal expectations model. A comparison between the ARFIMA model with a fractionally differenced ECM (column 1 of Table 4.8) and the standard ARIMA model (column 2) shows the substantial improvement gained by using fractional techniques.[19] Further, even though columns 1 and 3 differ only in so far as column 3's ECM is left in level form, there is some improvement in the more precise specification. Consistent with the findings of the Monte Carlo simulations in Chapters II and III, a comparison of the ECM’s coefficients and standard errors in columns 1 and 3 shows the tendency of these statistics to be biased downwards when the ECM is under-differenced. An encompassing test of the two models (Table 4.11) shows that the fractionally differenced ECM model clearly encompasses the level-form ECM (.01 level, t=2.83) while the latter barely fails to encompass the former (.05 level, t=1.94). Finally, column 4 of Table 4.8 shows the results of a one-step ECM procedure. J- tests find that column 1 encompasses its one-step rival (column 4, .01 level, t=2.82) and that column 4 fails to encompass column 1 (.05 level, t=1.90).

4.7 Conclusions

The multivariate ARFIMA model developed in this chapter provides clear support for the hypothesis that egocentric measures of the economy are better predictors of governing party support than are sociotropic measures. However, no clear winner is found between the personal expectations and personal retrospections models. It is quite possible that these two questions are so similar in the minds of respondents that no distinction between the two will emerge in multivariate analyses that include them. Nevertheless, the question of which variable is more relevant remains worthy of investigation. In terms of model choice, while the differences between results vary little among the various specifications employed here, it is important to note that the multivariate ARFIMA model with a fractionally differenced ECM outperforms every other specification while providing a more accurate picture of the dynamic relationships present within and between the variables.

The long memory methods described and demonstrated above provide a more accurate way of explaining the complex relationships between variables. ARFIMA modeling and fractional cointegration techniques allow us to more carefully construct complex multivariate models while simultaneously improving their accuracy and reducing threats to inference. Indeed, fractional dynamics in an error correction mechanism can present the same threats to inference posed by other fractionally integrated independent variables. Testing and accounting for the presence of long-memory in <u>all</u> variables and in the relationships among them should become necessary steps in the dynamic analyst's craft. In the next chapter, these techniques are applied to a model of presidential approval in the United States.

Endnotes

1. Looking for support for these expectations in estimates of *d* for the aggregated series would be an ecological fallacy, however. It is inappropriate to make conclusions about individual-level behavior based on aggregate data (Kramer 1983).

2. The following month, January, 1997, Gallup slightly changed its survey making one wary of including the final four months of data from the Conservatives' reign.

3. One advantage of fractional integration techniques is that it allows us to forgo the process of wading through the results of tests with limited null hypotheses of either d=1 or d=0 (Maddala and Kim 1998). Point estimates of *d* have become reliable enough that they can be used confidently and, along with estimated t-ratios, determine orders of integration (Barkoulas, Baum, and Caglayan 1999, Box-Steffensmeier and Tomlinson 1999). Nevertheless, standard stationarity test results are presented here.

4. Diebold (1989) actually presents two tests, the R test and the J (for joint) test. While the J test may be more appropriate for other alternatives such as explosive processes, the R test's assumption that $d \leq 1$ is proper for the series investigated here.

5. Bayesian techniques (Koop, Ley, Osiewalski, and Steel 1995) and robust testing with the bootstrap (Andersson and Gredenhoff 1998) have also been developed recently but are less appropriate here due to the relative wealth of time points (T=209).

6. See also Agiakloglou, Newbold, and Wohar (1993).

7. Prior to estimation, the variable of interest is differenced in order to dispense with the "troublesome intercept parameter" (Baillie 1996: 39). Differencing is also necessary because Sowell's estimator is incapable of estimating *d* when $d \geq .5$ (Box-Steffensmeier and Smith 1996: fn 28, 1998: fn 14). Differencing is also necessary prior to implementing Robinson's procedure in RATS.

8. RATS' Robinson's Gaussian Semiparametric Estimator procedure is also very easy to implement and as well as integrate into a longer program. Thus, it is Robinson's estimates of *d* that were used for the fractional differencing that precedes the multivariate models presented.

9. The AIC formula can be expressed as: AIC = -2*ln[log likelihood] + 2p. Where p is the number of independent parameters estimated. Hence, the AIC

favors more parsimonious models by increasing with each additional degree of freedom consumed. For a full discussion of the AIC see Chatfield (1996: 226). The SBC formula can be expressed as: SBC = -2*ln[log likelihood] + 2p(ln[T]) where T is the number of time points. Thus, the SBC imposes a slightly higher penalty for over-parameterized models. OX's Bayes' Information Criterion was also used and in every case favored the (0,*d*,0) models.

10. This is strictly true only for Conservative party support. For each of the other five variables a noise model with a lower AIC is possible. However, in every case there is a sound and obvious reason for favoring a (0,*d*,0) model. Aside from losing parsimony, the models with lower AICs had either multiple autoregressive parameters that summed greater than one, had multiple moving-average parameters that summed greater than one - or less than negative one -, or had non-significant autoregressive or moving-average parameters.

11. Among the advantages of fractional cointegration techniques is an ability to progress from low power tests of integration such as Dickey-Fuller (Diebold and Rudebusch, 1991) to analyses that incorporate the more precise *d* parameter.

12. Cheung and Lai (1993) and Box-Steffensmeier and Tomlinson (1998) explain that if the equilibrium errors are not mean reverting, i.e. $1 \leq d$, a permanent disequilibrium may result from a shock.

13. Requiring only that $s < d$ follows a broader definition of cointegration provided by Granger (1986) (Dueker and Startz 1998).

14. Barkoulas, Baum, and Oguz (1997; 9) state that "The error correction term could be I(*d*) with $0 < d < 1$, in which case deviations from equilibrium are persistent but the cumulative impulse response of a shock to the system equals zero at an infinite horizon. In this case, the error correction term follows a fractionally integrated process and the system's variables form a fractionally cointegrated system."

15. Enders (1995; 385) provides several reasons why a one-step procedure is preferable. Nevertheless, as a "multivariate generalization of the Dickey-Fuller test" (Enders, 1995; 386) it should not be surprising that the Johansen procedure loses effectiveness in the presence of fractional alternatives (see Diebold and Rudebusch 1991).

16. Traditional stationarity tests support the hypothesis that the ECM is fractionally integrated. For example, the Dickey-Fuller test rejects the null hypothesis of a unit-root process (.01) with a critical value of -5.88 and the variance ratio test rejects the null hypothesis of a random walk with drift (.05) with critical values of 2.208 (4 lags) 3.236 (8 lags).

17. The values estimated by Robinson's procedure were used.

18. One-step specifications were tried, i.e. governing party support (t-1) and prime ministerial approval (t-1) were included in a multivariate ARFIMA model of conservative party support. Comparing the results of the one-step regression with those of the two-step, the latter model outperformed the former in every respect (see Table 4.8, column 1 vs. column 4).

19. An encompassing test between these two models is impossible because the two do not have the same dependent variable. However, the ARIMA model was run with a fractionally differenced dependent variable and the model accounting for the fractional dynamics of all of its variables encompassed the model dealing only with the fractional dynamics of its dependent variable (.01 level, t=3.01). The latter did not encompass the former (.05 level, t=1.73).

CHAPTER V

FRACTIONAL INTEGRATION AND MODELS OF PRESIDENTIAL APPROVAL IN THE UNITED STATES

5.1 Introduction

As observed in Chapter III, multivariate models that account for the fractional character of all their variables outperform models that confine themselves to the dichotomous choice between stationarity and non-stationarity. Based on the Monte Carlo evidence of Chapters II and III, it also is evident that in the presence of fractional integration, inferences from ARFIMA models are more trustworthy than are those from simpler ARMA or ARIMA models. Here, the findings of previous chapters are applied to dynamic models of presidential approval in the United States during the 1978-97 period. As in Chapter IV, the possibility of fractional cointegration is tested. For the American data, however, no fractionally cointegrating relationships are found.

The chapter begins by reviewing the literature regarding factors that affect Americans' evaluations of their president. This is followed by a discussion of why one should expect time-series variables such as presidential approval and the components of the Index of Consumer Sentiment (ICS) to be fractionally integrated. Presidential approval and four subjective economic measures are tested for stationarity using the tests discussed in Chapter IV and estimates of the fractional differencing parameter, *d*, are derived for each series. Next, tests of fractional cointegration between presidential approval and the ICS variables are estimated. Following this, parameters in multivariate models of presidential approval are presented. Finally, encompassing tests are employed to address which subjective economic measure best explains presidential approval.

5.2 Peasants, Bankers and Presidential Approval

Mueller's (1970) path-breaking "Presidential Popularity from Truman to Johnson" argued that, *ceteris paribus*, a president's popularity was destined to diminish as time passed. Although his argument has since been dismissed as the "myth of inexorable descent" (Ostrom and Smith 1993), it remains important as the first serious analysis of the dynamics of presidential approval. Indeed, Mueller's finding that a president's popularity is dependent upon long-term trends and short-term events is a model that still dominates the literature. However, the economy and people's perceptions of it have long since replaced the inexorable descent thesis as factors believed to drive approval ratings (MacKuen 1983; Lewis-Beck 1988; MacKuen, Erikson, Stimson 1989, 1992; Clarke, Elliott, Mishler, Stewart, Whiteley, and Zuk 1992; Clarke and Stewart 1994).

MacKuen (1983) investigates the relationship between economics and presidential approval using the unemployment rate and the consumer price index as indicators of the nation's economic well-being. However, despite their salience, these two measures are merely two of several antecedent variables in the relationship between economics and political support (MacKuen, Erikson, and Stimson 1992). Of crucial importance to opinion formation is an individual's subjective evaluation of economic conditions. Using Granger causality tests (Enders 1995), MacKuen, Erikson, and Stimson (1992), show that the introduction of the ICS to analyses of presidential approval "wipes out the 'direct' contribution of the economic variables." Hence, the use of subjective perceptions of the economy such as the Index of Consumer Sentiment and its components allows researchers to delineate the links between objective economic conditions and political support.

MacKuen, Erikson, and Stimson (1992) use the components of the ICS to compare competing theories regarding which subjective evaluations have the strongest impact on presidential approval. Specifically, MES challenge Key's (1966) long-standing hypothesis that voters are retrospectively oriented and are most concerned with the state of their own pocketbooks. In their multivariate models of presidential approval, MES favor national expectations over national retrospections and personal expectations and retrospections, stating that "controlling for business expectations, no other measure of economic sentiment directly affects approval" (1992, 603). Thus, MacKuen and his colleagues claim voters are best described as "bankers" - sophisticated individuals who base their political judgements on how they expect the government to guide the economy in the future - rather than "peasants" whose evaluations are based on a "What have you done for me lately" mentality (1992, 597).

Clarke and Stewart (1994) argue that MacKuen, Erikson, and Stimson err by failing to test the quarterly presidential approval series and the quarterly economic measures for stationarity. Indeed, MES leave these variables in level form, thus implicitly assuming them to be stationary. Hence, Clarke and Stewart (1994) suggest that MES's finding that long-term national prospections dominate models of presidential approval may be a spurious result. Based on the results of Dickey-Fuller tests, Clarke and Stewart (1994) conclude that the measures of presidential approval, long- and short-term sociotropic expectations (good/bad in year ahead), and egocentric prospections are unit-root processes for the years 1954-92. Further, their Dickey-Fuller results suggest rejection of the unit-root hypothesis for a second short-term sociotropic prospects variable (better/worse) and for both egocentric and sociotropic retrospections. With values ranging between -2.12 and -3.93, these Dickey-Fuller results were all very near the critical value thresholds of -2.88 (.05 level) and -3.47 (.01 level) forcing the authors to make the knife-edged stationarity decision based on borderline evidence. Taking account of the stationarity of their variables, as decided by their Dickey-Fuller results, and using error correction specifications, Clarke and Stewart (1994) find that sociotropic retrospections as well as sociotropic prospections influence presidential approval.

Given that previous research has been unable to choose between the several subjective measures largely because of model choice, it is worthwhile to reconsider models of presidential approval in light of the possibility of fractional integration. Indeed, fractional integration is found to characterize presidential approval and all of the ICS series in both their quarterly and monthly forms

(Lebo, Walker, and Clarke (1998a). Establishing these series as being fractionally integrated is useful, first, because it provides insight into the dynamics that characterize the variables and, second, because it allows for more specific estimations of multivariate models that include them. Before presenting stationarity tests and multivariate ARFIMA models to answer the question of which subjective economic series best describes presidential approval, a brief discussion follows that considers the theoretical assumptions implicit in stationarity decisions and outlines why we should expect fractional dynamics to be present in the series of interest.

5.3 Fractional Dynamics and the American Case

The political researcher's decision to model a series either as a stationary, a unit-root, or a fractionally integrated process is not simply a matter of caprice or taste but, rather, entails important theoretical assumptions about the series of interest (Box-Steffensmeier and Smith 1998). Initial analyses of presidential approval such as Mueller (1970) and MacKuen (1983) argue that the presidential approval series was best characterized as a stationary, autoregressive series. By doing so, these authors assume that while political events or economic shocks may affect the movement of presidential approval in the short-run, these effects are merely temporary as the series returns to its long-run mean (DeBoef 1999).

At the other extreme, authors such as Ostrom and Smith (1993) who hypothesize that presidential approval is characterized as a unit-root process implicitly assume that any shocks to the series are permanent. Under this hypothesis, events have an additive effect and, rather than being forgotten, completely determine current approval ratings (DeBoef 1999). A unit-root series will tend to wander for long periods, has no true mean, and i's variance increases with the passage of time (Enders 1995; DeBoef 1999).

However, a fractionally integrated series accepts that individuals' reactions to shocks may not be homogenous. This follows theories of partisanship and other political attitudes such as Converse's (1964) black/white model and Key's (1966) switchers/stand-patters model. In this regard, Green and Palmquist's (1990) assertion that individual party identification is strongly persistent over time is likely true for a substantial portion of the electorate who will always return to their party of choice following a shock. For example, strong Republicans may have temporarily abandoned their party in the aftermath of Watergate, but the dissipation of this shock was evident in the election of Ronald Reagan as president in 1980 and in his landslide reelection of 1984. However, at the same time, partisanship will be transitory for another portion of the population. Always flexible, the current partisanship of the latter group will merely be the sum of their reactions to a long line of political events (Byers and Peel 1997). A series created by aggregating these two groups will be fractionally integrated with shocks lasting for long, yet finite, periods (Granger 1980). A fractionally integrated series will eventually exhibit mean reversion but any large segment of the series may appear to be a unit-root. This is precisely the type of behavior we should expect from the series under investigation here.

Additionally, as was the case for the British data discussed in Chapter IV (see section 4.3) the fact that the American series are aggregate-level data should lead us to expect fractional integration. Granger's (1980) finding that aggregating heterogenous individual-level behavior will produce a fractionally integrated series suggests that integer levels of integration are unlikely for the ICS variables and presidential approval. Indeed, all of these variables are created by adding together the survey responses of individuals possessing various autoregressive and moving average tendencies. Further, the fact that all of these series are bounded at both extremes is indicative of fractional dynamics as some long-term mean reversion is inevitable despite prolonged wanderings in the series' values (DeBoef and Granato 1997b). Thus, based on the statistical and theoretical reasons given above, we should expect tests of stationarity and estimates of *d* to reveal fractional dynamics in the American series.

5.4 Data, Tests of Stationarity, and Point Estimates of *d*

The monthly American data begin halfway through the term of President Carter, in January, 1978, and end halfway through the second term of President Clinton, in December, 1997. As such, the series cover a full 20 years, or 240 months. The first variable is monthly presidential approval, gathered by Gallup and calculated as the monthly percentage of people responding affirmatively to the question: "Do you approve or disapprove of the way ________ is handling his job as President?" The remaining four variables are subjective economic evaluations gathered to create the Index of Consumer Sentiment by the

University of Michigan’s Survey Research Center as part of its ongoing Survey of Consumer Finances and Survey of Consumer Attitudes and Behavior. These variables are:

(a) personal expectations (or prospections) - "Now looking ahead - do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

(b) personal retrospections - "Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

(c) national expectations (or prospections) - “Looking ahead, which would you say is more likely - that in the country as a whole we'll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what?"

(d) national retrospections - "Would you say that at the present time business conditions are better or worse than they were a year ago?"

Beginning with a base score of 100, each of these variables is constructed by adding the percentage of respondents offering a positive response and subtracting the percentage offering a negative response. Thus, each is an index bounded between 0 and 200 and created by aggregating individual-level behavior, characteristics that should immediately alert us to the possibility of fractional integration (Granger 1980; DeBoef and Granato 1997b). Multiple tests of stationarity and point estimates of *d* discussed below show that fractional dynamics are indeed present in each of these variables.

Table 5.1 shows the results of the Dickey-Fuller test (Dickey and Fuller

1979, 1981; see equation (4.1)) for the American data. Presidential approval rejects the unit-root hypothesis at the .05 level while personal expectations, personal retrospections, and national expectations do so at the .01 level. Only national retrospections fails to reject the unit-root hypothesis. While, these initial results suggest the presence of fractional integration, additional tests of stationarity using various null hypotheses were used to further diagnose the series.

The variance ratio test (Diebold 1989; see equation (4.2)) with a null hypothesis of a random walk with drift and an alternative hypothesis of pure fractional noise was the next test to be employed. As was the case with the British data, the variance ratio results shown in Table 5.2 are generally similar to the Dickey-Fuller results. Personal expectations, personal retrospections, and national expectations each reject ($p \leq .05$) the null hypothesis of a random walk with drift while national retrospections fails to reject the null. However, in contrast to the Dickey-Fuller results, however, the presidential approval variable fails to reject the random walk hypothesis. Taken together, the Dickey-Fuller results and the variance ratio results are unable to differentiate between fractional dynamics and stationarity. KPSS tests were thereby employed (Kwiatkowski, Phillips, Schmidt, and Shin 1992; see equation (4.3)) as an additional diagnostic tool.

The results of the first KPSS test, η_{μ}, are shown in Table 5.3. Recall from Chapter IV that the KPSS test tests the tendency of a series' autocorrelation function to decline at a constant rate (see equation 4.3). With the recommended lag truncation parameter of 4, each of the series rejects ($p \leq .05$) the null hypothesis of a stationary, strong mixing process. Based on these results, we cannot say that correlations between successive values of these series decline at a constant exponential rate. Hence, the autocorrelation functions of these series will die down slowly, a pattern indicative of fractional integration (Lo 1991).

The results of the second KPSS test, η_τ, establish that trend stationary processes do not describe these series (see Table 5.4). Here, every series soundly rejects the null hypothesis of a stationary, strong mixing process at the .01 level. Thus, the KPSS results, combined with those of the Dickey-Fuller tests and those of the variance ratio tests indicate that fractional dynamics may indeed describe these series.

A summary of these stationarity tests (Table 5.5) shows that presidential approval appears to be a fractionally integrated series. The same conclusion can be drawn for personal expectations, personal retrospections, and national expectations as each of these series rejects d=1 in one test and d=0 in another. Only national retrospections appears as though it may be a unit-root series. Based on these tests of stationarity, one should expect point estimates of the d parameter to reveal fractional dynamics at work in most, if not all, of these series.

The value of d was estimated for each of these series using both Sowell's (1992) and Robinson's (1995) estimators. As was done for the British data in Chapter IV, d was estimated for each variable in (p,d,q) models containing up to three autoregressive and three moving average parameters for a total of 16 models per variable. The Akaike Information Criterion (1973, 1974) and the

Schwartz Bayesian Criterion (Enders 1995) were used to distinguish which noise model best described each variable. As in Chapter IV, (0,*d*,0) models worked best in each case.

Table 5.6 shows the results of the *d* estimates for the (0,*d*,0) models. It is immediately evident that *d* does not equal 0 for any of these series. Presidential approval appears to be fractionally integrated but the unit-root hypothesis cannot be rejected ($p \leq .05$). The large t-statistic of 16.71 for rejection of the *d*=0 hypothesis indicates that researchers such as MacKuen (1983) and MacKuen, Erikson, and Stimson (1989, 1992) err by modeling presidential approval in level form, implicitly assuming it to be *d*=0. The same can be said for each of the four subjective economic measures for which rejection of the *d*=0 hypothesis is again easy with t-statistics ranging between 11.73 and 14.96. Rejection of the unit-root hypothesis is also possible for these series although this is only barely true for national retrospections (t=1.98). Based on these results, one can conclude that fractional dynamics characterize at least four, and likely all five, of these series. Thus, multivariate analyses that are to include these variables must account for this fractional integration. However, before fractionally differencing each variable, however, it is worthwhile to see if the use of an error correction mechanism is appropriate. Tests for cointegration and fractional cointegration presented next, however, show that no equilibrium relationship exists between presidential approval and the four subjective economic evaluations.

5.5 Tests for Fractional Cointegration

In Chapter IV, cointegration was explained as a long-term relationship between two or more variables (Granger 1981; Engle and Granger 1991; Beck 1993). Traditionally, a cointegrating relationship is said to exist between a system of variables if they each are non-stationary and some linear combination of the variables is stationary (Engle and Granger 1987; Banerjee, et al. 1993). Fractional cointegration relaxes the necessities of initial variables to be unit-roots and of the linear combination to be d=0 (Cheung and Lai 1993). Rather, the methodology of fractional cointegration requires the simpler concern of finding the level of integration for some linear combination of two variables to be lower than the level of integration for any one of the system's variables (Cheung and Lai; Dueker and Startz 1998). One advantage of the introduction of fractional cointegration is that it allows researchers to consider a wider range of behavior in the long-run relationships between variables.

In the standard method of cointegration, the existence of a cointegrating relationship between variables means that if a shock affects one, the system will be re-equilibriated as the variables return to their long-term relationship (Clarke, Stewart, and Whiteley 1997; Box-Steffensmeier and Tomlinson 1999). Fractional cointegration extends the methodology of cointegration by allowing for a wider range of behavior in this equilibrium relationship. Fractional integration in an equilibrium (error correction) term indicates that following a shock, the system of variables re-equilibriates at a rate slower than the exponential decay of an ARMA process (Barkoulas, Baum, and Oguz 1997). Next, the American data was tested in order to determine if any such relationships exist.

To test for the presence of cointegration and fractional cointegration, first, a cointegrating regression was performed between presidential approval and each of the four subjective economic measures and, second, the residuals (the error correction term) for each regression were tested for stationarity. The first cointegration test regressed presidential approval on personal expectations. As shown in Table 5.7, a Dickey-Fuller test on the residuals rejects the unit-root hypothesis (-3.54 versus a critical value of -3.46 at the .01 level). Based purely on this result, one might conclude that the residuals are stationary and that the two series cointegrate. However, an estimate of *d* for these residuals shows that this finding would be premature. Indeed, with a *d* value of .91 (s.e.=.056) the residual series is of a higher order of integration than is the personal expectations variable (*d*=.66) and is within a single standard error of the *d* value for the presidential approval variable (*d*=.94).

As Table 5.7 shows, this pattern repeats itself in the cointegrating regressions of personal retrospections, national expectations, and national retrospections. In each case, the Dickey-Fuller test results would have one conclude that the residual series is stationary but in no case is the *d* estimate for the residual series more than 1.4 standard errors below that of the presidential approval series. Further, in no case is the *d* estimate for the residual series below that of the original independent variable. Thus, not only do these results suggest that the presidential approval series does not cointegrate with any of the four subjective measures, they also demonstrate how likely it is that one could falsely accept the cointegration hypothesis by relying exclusively on Dickey-Fuller results.

This failure to find evidence of cointegration shows that none of the subjective economic variables move closely with presidential approval over the long-run. Unlike the relationship between prime ministerial satisfaction and governing party support in Britain discussed in Chapter IV, no long-term equilibriating relationship was found between presidential approval and any of the economic measures. Thus, one can conclude that presidential approval and the economic measures are not as closely aligned as are prime ministerial satisfaction and governing party support in Great Britain. The absence of cointegrating or fractionally cointegrating relationships between the American series indicates that the use of error correction mechanisms are inappropriate for the data. Thus, multivariate analyses of presidential approval can begin by simply fractionally differencing each of the variables by its own d value. These multivariate ARFIMA models are presented next.

5.6 Multivariate Models of Presidential Approval

I now consider multivariate models of presidential approval in the United States for the years 1978-1997. To begin, presidential approval and each of the four subjective economic evaluations was fractionally differenced by its own d value (see Table 5.6) in order to render each d=0. As just discussed, the absence of cointegrating relationships between any of the economic variables and presidential approval determined that error correction mechanisms were inappropriate.

Next, several interventions were included as independent variables to account for the impact of events on presidential approval. These events were: the taking of American hostages in Iran (November, 1979), the failure of the attempt to rescue the hostages in Iran and the subsequent frustration with America's continued inability to free them (March, 1980 - November, 1980), President Reagan's term in office (January, 1981 - December, 1988), the attempted assassination of Ronald Reagan (March, 1981 - May, 1981) the Iran-Contra scandal during President Reagan's second term in office (November, 1986 - December 1988), President Bush's term in office (January, 1989 - December, 1992), the Tienanmin Square incident (June, 1989), and operation Desert Storm (January, 1991). Finally, an additional variable, EVENTS, is used to capture expected shifts in public opinion due to miscellaneous political and economic events.

To ensure equation balance (see Phillips 1986; DeBoef and Granato 1997b), each of these interventions was differenced to the same extent (0.94) as was the dependent variable, presidential approval. This follows the standard admonition that what one does to the left-hand-side variable in a Box-Jenkins-Tiao (1977) intervention model, one must also do to the right-hand-side intervention variables. Figures 5.1 and 5.2 show the slight difference between an intervention that has been differenced wholly and differenced fractionally.

Presidential approval - fractionally differenced - was used as the dependent variable in the four separate analyses shown in Table 5.8. Column 1 of Table 5.8 shows personal expectations are statistically significant ($p \leq .05$) along with the intervention variables. Column 2 shows that, contrary to Key's pocketbook hypothesis, personal retrospections are not significant. Columns 3 and 4 show each of national expectations and national retrospections are statistically significant ($p \leq .01$). Thus, contrary to the findings of the British analyses in Chapter IV, in the American case, sociotropic measures outperform egocentric measures. The J-test for encompassing (Mizon 1984; Mizon and Richard 1986) shown in Table 5.10 further demonstrates the superiority of the national expectations model as it encompasses the personal expectations model (.01 level) while personal expectations fails to encompass national expectations (.05 level).

As for the two sociotropic measures, Table 5.8 shows that national prospections are a slightly better predictor of presidential approval than are national retrospections ($t = 4.23$ vs $t = 3.64$). These findings support those of Clarke and Stewart (1994) who argue, contrary to MacKuen, Erikson, and Stimson (1992), that national retrospections, as well as expectations, are valuable as predictors of presidential approval. Including both national prospections and national retrospections in the same model yields t-statistics of 2.78 and 1.81, respectively. However, the J-test for encompassing (Table 5.11) finds that the national expectations model encompasses the national retrospections model (.01 level) while the national retrospections model fails to encompass the national expectations model (.05 level). These findings indicate that while national prospections are a better predictor of presidential approval, some additional predictive power is gained by including the national retrospections variable. Indeed, the finding that voters think like bankers, using opinions regarding future national economic performance to evaluate their president, must be tempered by the understanding that, mindful of the recent past, perhaps many bankers are somewhat peasants.

The efficacy of the ARFIMA techniques used to estimate the rival models was also tested. Column 2 of Table 5.9 shows a national prospections model that uses wholly differenced interventions while column 1 shows the national prospections model of Table 5.8. Although slight, there is a noticeable improvement when the interventions are differenced to the same degree as the dependent variable rather than wholly differenced. Moving from the wholly differenced intervention model to the fractionally differenced one, R^2 increases from .494 to .503, and the sum of squared residuals decreases from 2411.7 to 2368.8. An encompassing test of the two models (Table 5.12) further demonstrates the value of maintaining precise equation balance as the model with fractionally differenced interventions encompasses the one with wholly differenced interventions ($p \leq .01$) while the former model fails to encompass the latter ($p \leq .05$).

Finally, comparing the ARFIMA model of column 1 with the ARIMA model of column 3, the benefits of the ARFIMA approach again are demonstrated. Moving from the ARIMA model to the ARFIMA, R^2 increases from .491 to .503

and the sum of squared residuals decreases from 2,423.8 to 2,368.8. Additionally, the more precise ARFIMA specification suggests a much stronger link (b = 0.121) between national expectations and presidential approval than does the ARIMA model (b = 0.088). Thus, estimates derived from the ARFIMA approach seem to show stronger support for the bankers hypothesis than do estimates derived for ARIMA models.

5.7 Conclusions

Converse's (1964) black/white model and Key's (1966) switchers/stand-patters model suggest that the American electorate is composed of individuals with various autoregressive tendencies present in their voting behavior. Granger's (1980) demonstration that aggregating heterogenous individual-level data will create a fractionally integrated series should lead one to suspect the presence of fractional dynamics in series such as aggregate presidential approval and the components of the ICS. Indeed, estimates of d obtained for the American data indicate that these variables are fractionally integrated. Based on the simulation evidence of Chapters II and III, these variables were rendered d=0 through fractional differencing prior to their inclusion in multivariate models. Tests of relationships between presidential approval and each of the subjective evaluations found little evidence of cointegrating or fractionally cointegrating relationships. Thus, error correction mechanisms were deemed inappropriate for the American presidential approval models.

Regarding short-run relationships between the variables, the multivariate

ARFIMA models show clear support for the hypothesis that aggregated sociotropic measures of the economy are better predictors of presidential approval than are egocentric measures. This finding is in contrast with the British case of Chapter IV where egocentric measures were found to dominate sociotropic ones. Further, comparing the sociotropic measures, expectations were found to dominate retrospections although both are significant when used jointly in the presidential approval model. Precisely accounting for the level of integration of all of their variables, these ARFIMA models allow a greater deal of confidence in their estimates than do ARIMA specifications. Future work should apply the techniques described in this and previous chapters to the development and testing of multivariate models of other political attitudes and behavior. Box-Steffensmeier and Smith's (1998) multivariate ARFIMA model of macropartisanship was a significant step in enhancing understanding of factors that affect aggregate dynamics of party identification in the American electorate. Building upon the methods of Box-Steffensmeier and Smith by including those discussed in this and previous chapters will allow future researchers to better understand the dynamic relationships present both within and between their variables.

Endnotes

1. Clarke and Stewart (1994) do allow for the possibility that these series could be fractionally integrated but they do not test for it (1007; footnote 4).

2. Individual behavior is not confined to these two groups, however. These are merely endpoints in a continuum of autoregressive behavior.

3. Two additional variables that measure short term national expectations are used as components of the ICS. The first asks, "Generally speaking, do you think now is a good or a bad time for people to buy major household items?" The second asks, "Now turning to business conditions in the country as a whole - do you think that during the next 12 months we'll have good times financially, or bad times or what?" MacKuen, Erikson, and Stimson (1992) found that the long-term measure of national expectations dominated the short-term measures in multivariate analyses. Clarke and Stewart (1994) also favor the long-term measure and thus, only the long-term measure is used in the analyses here. Tests of stationarity and estimates of d did show each of these short-term measures to be fractionally integrated with $d = .88$ for buying conditions good/bad and $d = .83$ for business conditions (see also Lebo, Walker, and Clarke (1998a) for a discussion of the memory of these, and other, series).

4. Unlike national expectations and personal expectations and retrospections, this variable is not a component of the ICS.

5. Note that MacKuen, Erikson, and Stimson (1989, 1992) use a quarterly measure of presidential approval in their analyses. This quarterly measure has been found to be fractionally integrated as well with d in the 0.89 - 0.93 range (Lebo, Walker, and Clarke 1998a).

6. Tests for multiple cointegrating vectors were also performed. Every combination of the four independent variables was regressed on presidential approval. The d values for the residuals of these 15 regressions were estimated and none were significantly lower than the d value of presidential approval (0.94).

7. Clarke and Stewart (1994) use of ECMs cannot be rejected here as they used quarterly data. Tests for fractional cointegration between these quarterly measures could prove the use of a fractionally integrated ECM (see Chapter IV) to be appropriate for their data.

8. The values estimated by Robinson's (1995) procedure were used.

9. This period also corresponds to the Soviet invasion of Afghanistan.

10. By applying the fractional differencing filter to interventions, we can model shocks so that they affect the dependent variable not only in the first period, but well beyond. Thus, long-memory is introduced into the intervention variable. The degree to which this occurs depends on the degree of memory in the dependent variable. Here, with d = .94, a series coded as ...0,1,0... becomes ...0,1,-1,0... in differenced form and becomes ...0,1,-0.940,-0.028,-0.010,-0.005... when fractionally differenced.

11. When all four of the subjective variables were included in the same model, the personal measures were not statistically significant and national prospections (t=2.67) outperformed national retrospections (t=1.57).

12. With different dependent variables, we cannot speculate as to whether this difference is statistically significant.

CHAPTER VI

CONCLUSION:

FRACTIONAL INTEGRATION AND POLITICAL MODELING

The introduction of fractional dynamics to political scientists is only just beginning to have effects on the political modeler's craft. Granger's (1980) initial warning that fractional integration is a likely result when the behavior of heterogenous individuals is aggregated was long ignored by researchers who used data constructed precisely in that way. However, with their 1996 *American Political Science Review* article, "The Dynamics of Aggregate Partisanship," Box-Steffensmeier and Smith finally alerted political researchers that the knife-edged distinction between stationary (I(0)) and random walk (I(1)) behavior is an arbitrary one that fails to account for the true behavior of data generating processes that create political variables. Lebo, Walker, and Clarke (1998a) followed Box-Steffensmeier and Smith by demonstrating that fractional integration is actually quite common among popular political time series. Then, as DeBoef and Granato (1997a) did for the near-integrated case, Lebo, Walker, and Clarke demonstrate that including untransformed fractionally integrated series in bivariate regressions creates serious threats to inference by prompting a tremendous increase in the false rejection rate of null hypotheses. It remained to be demonstrated how a political researcher using fractionally integrated data should proceed in analyses of the relationships between two or more fractionally integrated variables.

This dissertation has been concerned with developing and demonstrating techniques for including fractionally integrated variables in complex models of political relationships. Based upon previous research and the analyses presented above, it is apparent that time-series analysts need to include fractional integration techniques as part of their standard operating procedure. The several steps of this new process are outlined below.

First, researchers must recognize that the method by which many political variables are constructed is likely to produce a fractionally integrated series. The heterogeneity Granger (1980) refers to is in the autoregressive tendencies of individuals in the sample population. Certainly it is easy to apply this scenario to political variables. Converse's (1964) black/white model and Key's (1966) division of voters into stand-patters and switchers delineate two types of individuals with autoregressive tendencies of unit-root and stationary behavior, respectively (see also Clarke, Jenson, LeDuc, and Pammett 1979, and; Clarke and McCutcheon 1998). If the population was made up only of individuals of these two groups, the autocorrelation function of a series that aggregated their behavior would show that the choices of the stand-patters were remembered perfectly from one period to the next while those of the "white" switchers (0,0,0) would be independent of their previous behavior. As such, correlations across long lags would be visible and fractional integration would be present.

That autoregressive tendencies of varying strength exist within the general population and among survey respondents should not be surprising although its applicability to measures of partisanship is unsettling for some who view an individual's partisanship as an unchanging character trait (see Green and Palmquist 1990). Accepting Zaller's (1992) conception of political knowledge as being normally distributed in mass publics we can see that for those with little knowledge, a change of mind can be based on the slightest bit of new information while for those in the other tail of the knowledge distribution, opinions will be highly persistent.

The highly knowledgeable may hold unshakable opinions of leaders and parties based upon years of loyalty while the approval of others is tenuous enough to change based upon the latest evening news sound-bite. When the perfect memory, or unit-root behavior, of the highly knowledgeable is amalgamated with the "top of their heads" (Taylor and Fiske 1978), or stationary (i.e. $X_t = \epsilon_t$ and $\epsilon \sim N(o,\sigma^2)$) behavior of others, as well as with the wide array of autoregressive behaviors among those in the middle of the distribution, a fractionally integrated series is born. Of key importance is that for series created through aggregation, only homogeneity at the individual-level makes integer levels of integration possible. Given the low likelihood that this assumption will hold, political scientists should expect to habitually find fractional dynamics characterize their aggregate time series data.

Once analysts recognize the prevalence of fractional integration, they will need to familiarize themselves with the ARFIMA techniques presented in this dissertation and elsewhere in the time series literature (especially Granger 1980; Baillie 1996; Cheung and Lai 1993; Box-Steffensmeier and Smith 1996, 1998; Abadir and Taylor 1998). The first tools that should be learned are estimation procedures for the *d* parameter such as those of Sowell (1992) and Robinson (1995) discussed in Chapter IV. These procedures allow us to dispense with the tedious task of sorting through several dichotomous tests of stationarity (Maddala and Kim 1998) by providing a precise estimate of the order of integration.[1] This estimate may then be used to filter the original series in order to generate a new fractionally differenced series for which d=0.

Chapters II and III demonstrate that by using these transformed variables, threats to inference produced by fractional dynamics are minimized. Lebo, Walker, and Clarke (1998b) demonstrate that the inclusion of untransformed fractionally integrated variables in bivariate regression may increase the likelihood of obtaining spurious results by a factor of 15. Chapters II and III herein demonstrate through Monte Carlo evidence that rather than leaving them untransformed, fractionally differencing each variable in an equation by its own estimate of *d* will minimize the rate of type I errors as well as avoid the biasing of Durbin-Watson statistics, standard errors, and coefficients that can wreak havoc on inferences.

Chapters II and III also test fractional differencing against the alternative of over-differencing. These simulations confirm that over-differencing the dependent variable introduces autocorellation into the equation. Short-term moving-average components can be used to model out this autocorrelation but only at the expense of type I errors and the over-inflation of model diagnostics. Monte Carlo evidence also confirms that over-differencing independent variables biases downwards coefficient and standard error estimates. Thus, only by differencing each variable in an equation by its precise value of *d* can one ensure that no bias exists towards autocorellation or in the estimation of standard errors and regression coefficients. Absent these biases, analysts can be more secure that when they find a significant relationship between variables, it is real rather than nonsense (Yule, 1926).

This dissertation also has explored the concept of fractional cointegration as a method for more precisely dealing with relationships among variables. The possibility that long-run equilibrium relationships between variables may be fractional processes implies the necessity of rethinking the methodology of cointegration. Dispensing with the assumption that the equilibrium term is I(0), the analyst can be satisfied that two or more variables cointegrate if their errors are simply mean reverting and of a lower order of integration than are any of the original variables. Expanding cointegration in this way allows for a greater variety of equilibriating behavior and makes sense theoretically.

For the British case, the finding in Chapter IV that prime ministerial approval and governing party support are fractionally cointegrated means that after a shock to one variable, the two variables will return to an equilibrium at some non-geometric rate. In political terms, this means that if some shock - such as a cabinet scandal or the introduction of a highly unpopular measure like the poll tax in Great Britain in the spring of 1990 - should affect peoples' perceptions of the prime minister, voters will adjust their opinions of the governing party at different rates. Some voters may retain their partisan attachments but may never forgive the prime minister while others quickly adjust their partisanship decisions to be more in tune with their opinion of the country's leader. First understanding that with the possibility of fractional integration, equilibrium terms can follow more diverse behavior and, second, acquiring the tools for assessing this wider range of behavior should become priorities for the political analyst.

Using these new techniques Chapter IV investigates competing models of governing party support. Conservative vote intentions, prime ministerial approval, and four subjective economic measures were tested and each was found to be fractionally integrated. After fractionally differencing each and after creating a fractionally differenced error correction mechanism, models were developed to determine which of personal expectations, personal retrospections, national expectations, or national retrospections was the best predictor of Conservative vote intentions for the years 1979-1996. Support for the arguments of Key (1966) and Sanders (1991) is found as it is shown that egocentric measures outperform sociotropic ones. However, no clear winner could be found between personal expectations and personal retrospections. Encompassing tests also were shown to be incapable of choosing between the two personal economic evaluation measures. Besides the economic measures and prime ministerial approval, each of the elections of 1983 and 1992, the Falklands War, the introduction of the poll tax, and the beginning of John Major's tenure as prime minister had significant impacts on levels of support for the governing party. These findings are in line with those of previous studies and thus bolster the general conclusion that governing party support in Britain is driven by a combination of economic and political factors.

The techniques investigated in Chapters II and III are again applied in Chapter V with a model of presidential approval in the United States for the period 1978-1997. Tests of stationarity and estimates of *d* were applied to presidential approval and to four subjective economic variables and each was found to be fractionally integrated, although presidential approval is found to be very near to a unit-root process. Again, prospective and retrospective evaluations of the national economy are compared with perceptions of personal finances. However, for the American case, sociotropic evaluations are found to dominate egocentric measures. This finding supports the arguments of MacKuen, Erikson, and Stimson (1992) rather than those of Key (1996). MacKuen Erikson, and Stimson's further argument that national expectations are a better predictor of presidential approval than are national retrospections is also supported by the evidence provided by the fractional models. Despite their value as predictors tests for cointegration and fractional cointegration between the four subjective measures and presidential approval fails to find the existence of fractionally and wholly cointegrating relationships.

In sum, this dissertation has sought to investigate various techniques for dealing with fractionally integrated variables in multivariate models of the dynamics of political attitudes and behavior. Researchers should note the threats to inference that can be avoided by careful use of fractional differencing. Also, the greater flexibility of equilibrium behavior provided by fractional cointegration should be helpful to those studying closely related variables. Avoiding the dichotomous distinction of stationarity versus random walk behavior allows us to understand the univariate characteristics of our variables and to then incorporate this understanding into more complex models. Dispensing with dichotomous tests such as Dickey-Fuller also will allow a greater degree of precision in our diagnoses. Perhaps from this, the hopes of the LSE school can be reached: that two rival modelers with the same data can gradually hone in on the same conclusions regarding what processes drives their variables. In sum, fractional integration techniques provide political scientists with an enhanced ability to explain not only the dynamic properties of their variables, but the relationships between them as well.

Endnotes

1. Sowell's technique in OX is especially useful because it allows the estimation of *d* in (*p*,*d*,*q*) models. Thus, we can estimate short-term and long-term components simultaneously. Robinson's procedure in RATS is useful for estimation of *d* in (0,*d*,0) models and for confirming estimates given by Sowell's estimator. The use of other estimators such as Bayesian techniques or Bootstrap methods can prove useful if data is especially sparse or if we adhere to Hendry's (1995) admonition to "test, test, test."

APPENDIX A

RATS PROGRAMS AND SEED VALUES FOR BIVARIATE SIMULATIONS

Appendix A

RATS Programs and Seed Values for Bivariate Simulations

RATS Program for Chapter 2 Simulation 1:

```
end 1
allocate 50000
dec vector coeff(1000) tstat(1000) dwstat(1000) stderrs(1000) rsq(1000)
dec real ja ka d1 d2 d1a d2a
open(APPEND) copy c:\ch2sim1.out
frequency 1 1000
source(noecho) c:\estima.src\xgamma.src
source(noecho) c:\estima.src\arfsim.src
source(noecho) c:\estima.src\fif.src
seed 59123
compute n = 150
do J=1,10
 compute ja = (J * .1)
 compute d1 = ja
 display 'd1 is equal to ' d1 '.'
do K=1,10
 compute ka = (K * .1)
 compute d2 = ka
display 'd2 is equal to ' d2 '.'
do I=1,1
 @arfsim d1 n simvar1
 @arfsim d2 n simvar2
 {
if d1>.4
 {
  set simvar1b = simvar1 - simvar1{1}
  compute d1a = d1 - 1
 }
else
 {
  set simvar1b = simvar1
  compute d1a = d1
 }
end if
 {
```

```
 {
if d2>.4
 {
  set simvar2b = simvar2 - simvar2{1}
  compute d2a = d2 - 1
 }
else
 {
  set simvar2b = simvar2
  compute d2a = d2
 }
end if
 }
```
** Application of the fractional differencing procedure (fif) was selectively applied depending on the simulation. In some cases first-differencing was used rather than fractional differencing.*
```
 @fif(d=d1a) simvar1b / simvar1a
 @fif(d=d2a) simvar2b / simvar2a
 linreg simvar1a / simres1
 # constant simvar2a
 compute coeff(I) = %BETA(2)
 compute dwstat(I) = %DURBIN
 compute stderrs(I) = sqrt(%SEESQ * %XX(2,2))
 compute rsq(I) = %RSQUARED
 compute tstat(I) = abs(coeff(I) / stderrs(I))
 display(unit=copy) coeff(I) stderrs(I) tstat(I) dwstat(I) rsq(I)
end do I
end do K
end do J
close copy
```

Seed Values used for Random Sampling*:

Control Simulation: 39185.
Simulation 1: 59123.
Simulation 2: 74623.
Simulation 3: 15824.
Simulation 4: 49175.
Simulation 4A: 49175.
Simulation 5: 38459.
Simulation 5A: 38459.
Simulation 6: 73375.
Simulation 6A: 73375.
Simulation 6B: 73375.
Simulation 6C: 73375.

Simulation 6D: 73375.
Simulation 6E: 73375.
Simulation 6F: 73375.

* These numbers were chosen randomly and are provided to allow exact replication of Chapter II's simulations.

APPENDIX B

RATS PROGRAMS AND SEED VALUES FOR MULTIVARIATE SIMULATIONS

Appendix B

RATS Programs and Seed Values for Multivariate Simulations

RATS Program for Chapter 3 Simulation 1:

```
end 1
allocate 50000
dec vector coeff1(1000) tstat1(1000) dwstat(1000) stderrs1(1000) rsq(1000)
coeff2(1000) stderrs2(1000) tstat2(1000)
dec real ja ka d1 d2 d1a d2a d3 d3a
open(APPEND) copy c:\ch3sim11.out
frequency 1 150
source(noecho) c:\xgamma.src
source(noecho) c:\arfsim.src
source(noecho) c:\fif.src
seed 28723
compute n = 150
compute d3 = .1
do J=1,10
 compute ja = (J * .1)
 compute d1 = ja
 display 'd1 is equal to ' d1 '.'
do K=1,10
 compute ka = (K * .1)
 compute d2 = ka
display 'd2 is equal to ' d2 '.'
do I=1,1000
 @arfsim d1 n simvar1
 @arfsim d2 n simvar2
 @arfsim d3 n simvar3
 {
if d1>.4
 {
  set simvar1b = simvar1 - simvar1{1}
  compute d1a = d1 - 1
 }
else
 {
  set simvar1b = simvar1
  compute d1a = d1
```

```
 }
end if
 {
 {
if d2>.4
 {
  set simvar2b = simvar2 - simvar2{1}
  compute d2a = d2 - 1
 }
else
 {
  set simvar2b = simvar2
  compute d2a = d2
 }
end if
 }
{
if d3>.4
 {
  set simvar3b = simvar3 - simvar3{1}
  compute d3a = d3 - 1
 }
else
 {
  set simvar3b = simvar3
  compute d3a = d3
 }
end if
* Application of the fractional differencing procedure (fif) was selectively applied
depending on the simulation.
@fif(d=d1a) simvar1b / simvar1a
@fif(d=d2a) simvar2b / simvar2a
@fif(d=d3a) simvar3b / simvar3a
 linreg(NOPRINT) simvar3a / simres3
 # constant simvar1a simvar2a
 compute coeff1(I) = %BETA(2)
 compute dwstat(I) = %DURBIN
 compute stderrs1(I) = sqrt(%SEESQ * %XX(2,2))
 compute rsq(I) = %RSQUARED
 compute tstat1(I) = abs(coeff1(I) / stderrs1(I))
 compute coeff2(I) = %BETA(3)
 compute stderrs2(I) = sqrt(%SEESQ * %XX(3,3))
 compute tstat2(I) = abs(coeff2(I) / stderrs2(I))
display(unit=copy) coeff1(I) stderrs1(I) tstat1(I) dwstat(I) rsq(I) coeff2(I)
stderrs2(I) tstat2(I)
```

```
end do I
end do K
end do J
close copy
```
** The above was repeated for d3 = .2, .3, .4, .5, .6, .7, .8, .9, and 1.0.*

Seed Values used for Random Sampling:

Control Simulation: 15680.
Simulation 1:
d(Y) = 0.1: 28723.
d(Y) = 0.2: 97315.
d(Y) = 0.3: 67984.
d(Y) = 0.4: 35412.
d(Y) = 0.5: 18354.
d(Y) = 0.6: 76544.
d(Y) = 0.7: 25974.
d(Y) = 0.8: 79438.
d(Y) = 0.9: 10941.
d(Y) = 1.0: 47211.

Simulation 2:
d(Y) = 0.1: 35814.
d(Y) = 0.2: 98362.
d(Y) = 0.3: 69411.
d(Y) = 0.4: 24874.
d(Y) = 0.5: 75136.
d(Y) = 0.6: 91843.
d(Y) = 0.7: 55872.
d(Y) = 0.8: 23783.
d(Y) = 0.9: 33597.
d(Y) = 1.0: 48462.

Simulation 3:
d(Y) = 0.1: 34617.
d(Y) = 0.2: 15645.
d(Y) = 0.3: 28771.
d(Y) = 0.4: 68159.
d(Y) = 0.5: 84772.
d(Y) = 0.6: 62371.
d(Y) = 0.7: 56715.
d(Y) = 0.8: 94579.
d(Y) = 0.9: 82713.
d(Y) = 1.0: 35456.

Simulation 4:
d(Y) = 0.1: 37617.
d(Y) = 0.2: 75895.
d(Y) = 0.3: 50076.
d(Y) = 0.4: 73059.
d(Y) = 0.5: 93510.
d(Y) = 0.6: 32487.
d(Y) = 0.7: 25863.
d(Y) = 0.8: 35102.
d(Y) = 0.9: 95588.
d(Y) = 1.0: 77548.

Simulation 5:
d(Y) = 0.1: 70958.
d(Y) = 0.2: 20451.
d(Y) = 0.3: 32870.
d(Y) = 0.4: 35258.
d(Y) = 0.5: 98102.
d(Y) = 0.6: 11057.
d(Y) = 0.7: 67621.
d(Y) = 0.8: 47417.
d(Y) = 0.9: 76632.
d(Y) = 1.0: 82150.

TABLES

Table 2.1 Summary Statistics for Control Simulation

Variable	N	Mean	Std. Dev.	Min.	Max
X-Coef	100,000	0.0003	0.0825	-0.3949	0.3775
X-Stderr	100,000	0.0822	0.0068	0.0543	0.1164
D-W Stat	100,000	1.9990	0.1628	1.3655	2.7565
R^2	100,000	0.0067	0.0094	0.0000	0.1151
TypeOne	100,000	0.0516	0.2213	0.0000	1.0000
|X-Coef|	100,000	0.0657	0.0499	0.0000	0.3949
T-Stat	100,000	0.0034	1.0061	-4.3239	4.3878
|T-Stat|	100,000	0.8013	0.6085	0.0000	4.3878

Table 2.2 Simulation 1: Type I Errors by *d* Values of X and Y

d value for dep. variable, Y	*d* value for independent variable - X										
	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	48	59	57	50	42	62	61	45	55	50	529
.2	62	52	44	52	52	60	63	51	54	54	544
.3	51	52	46	43	57	52	57	47	48	59	512
.4	50	55	43	58	52	61	58	61	50	53	541
.5	49	49	37	57	48	45	47	46	42	53	473
.6	61	46	59	49	41	52	55	43	60	58	524
.7	59	51	56	57	**77**	54	40	47	52	50	543
.8	45	48	47	51	**64**	49	60	59	59	56	538
.9	44	43	41	47	58	47	57	61	42	44	484
1	45	51	43	58	52	54	40	50	47	53	493
Totals	514	506	473	522	543	536	538	510	509	530	5181

Bold figures are statistically distinguishable from 50 (.05).

Table 2.3 Simulation 2: Type I Errors by *d* Values of X and Y

d value for dep. variable, Y	*d* value for independent variable - X .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	47	**67**	52	43	60	50	52	48	45	50	514
.2	**68**	57	51	52	49	58	53	44	50	57	539
.3	57	62	51	52	52	60	54	**66**	61	**64**	579
.4	57	53	50	63	61	**71**	**78**	**72**	**76**	**82**	663
.5	52	56	52	41	50	57	**64**	**69**	**74**	**70**	585
.6	46	49	49	52	58	59	59	**73**	63	49	557
.7	47	41	48	54	55	56	48	52	42	47	490
.8	47	52	47	60	51	54	60	49	**32**	55	507
.9	41	41	46	57	56	55	52	48	48	52	496
1	53	62	**64**	53	61	53	55	55	45	41	542
Totals	515	540	510	527	553	573	575	576	536	567	5472

Bold figures are statistically distinguishable from 50 (.05).

Table 2.4 Untransformed Fractionally Integrated Variables:
Type I Errors by *d* Values of X and Y, N=100 for Each Series.

d value for dep. variable, Y	*d* value for independent variable - X										
	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	56	**65**	**67**	**67**	**97**	**109**	**124**	**112**	**116**	**137**	950
.2	63	**70**	**77**	**121**	**125**	**167**	**189**	**208**	**241**	**229**	1490
.3	54	**71**	**135**	**160**	**202**	**220**	**287**	**302**	**328**	**337**	2096
.4	**80**	**107**	**173**	**201**	**241**	**306**	**345**	**378**	**422**	**413**	2666
.5	**84**	**134**	**182**	**260**	**301**	**387**	**416**	**453**	**493**	**558**	3268
.6	**84**	**152**	**219**	**302**	**400**	**441**	**506**	**568**	**583**	**604**	3859
.7	**99**	**180**	**268**	**331**	**458**	**529**	**569**	**623**	**642**	**672**	4371
.8	**124**	**220**	**317**	**384**	**478**	**547**	**622**	**650**	**691**	**691**	4724
.9	**108**	**231**	**333**	**409**	**520**	**584**	**629**	**704**	**715**	**704**	4937
1	**131**	**237**	**320**	**445**	**513**	**587**	**651**	**693**	**761**	**742**	5080
Totals	883	1467	2091	2680	3335	3877	4338	4691	4992	5087	33441

Bold figures are statistically distinguishable from 50 (.05).

Source: Lebo, Walker, and Clarke (1998b; Table 6).

Table 2.5 Simulation 2: Standard Errors by *d* Values of X and Y

d(Y)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.082	0.080	0.077	0.071	0.064	0.054	0.045	0.036	0.028	0.020	0.056
.2	0.082	0.080	0.076	0.071	0.064	0.054	0.045	0.036	0.027	0.021	0.056
.3	0.082	0.080	0.076	0.071	0.063	0.055	0.045	0.036	0.028	0.020	0.056
.4	0.082	0.080	0.076	0.071	0.064	0.055	0.045	0.036	0.028	0.020	0.056
.5	0.082	0.080	0.076	0.071	0.063	0.055	0.045	0.036	0.027	0.021	0.056
.6	0.082	0.080	0.077	0.071	0.064	0.054	0.045	0.036	0.027	0.020	0.056
.7	0.082	0.080	0.076	0.071	0.063	0.055	0.045	0.035	0.028	0.020	0.056
.8	0.082	0.080	0.076	0.071	0.063	0.054	0.044	0.036	0.028	0.020	0.056
.9	0.082	0.079	0.076	0.071	0.063	0.055	0.044	0.036	0.027	0.020	0.056
1	0.082	0.080	0.076	0.071	0.063	0.055	0.045	0.036	0.027	0.020	0.056
Mean	0.082	0.080	0.076	0.071	0.063	0.055	0.045	0.036	0.028	0.020	0.056

Table 2.6 Simulation 2: Absolute Value of Coefficients by *d* Values of X and Y

d(Y)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.064	0.064	0.060	0.058	0.052	0.043	0.035	0.030	0.021	0.016	0.044
.2	0.067	0.065	0.060	0.057	0.050	0.045	0.036	0.028	0.022	0.017	0.045
.3	0.065	0.064	0.061	0.057	0.051	0.046	0.035	0.031	0.022	0.017	0.045
.4	0.066	0.063	0.059	0.059	0.053	0.046	0.039	0.031	0.024	0.017	0.046
.5	0.066	0.064	0.062	0.055	0.051	0.045	0.038	0.030	0.023	0.017	0.045
.6	0.064	0.063	0.061	0.058	0.051	0.044	0.038	0.030	0.023	0.016	0.045
.7	0.064	0.061	0.058	0.058	0.050	0.044	0.036	0.029	0.022	0.016	0.044
.8	0.065	0.065	0.061	0.057	0.049	0.044	0.036	0.028	0.021	0.016	0.044
.9	0.064	0.064	0.060	0.056	0.051	0.044	0.035	0.028	0.022	0.016	0.044
1	0.065	0.065	0.061	0.055	0.052	0.044	0.036	0.029	0.022	0.016	0.044
Mean	0.065	0.064	0.060	0.057	0.051	0.044	0.036	0.029	0.022	0.016	0.045

Table 2.7 Simulation 4: Durbin-Watson Values by *d* values of X and Y

	d(X)										
d(Y)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	2.916	2.917	2.911	2.910	2.918	2.918	2.916	2.913	2.915	2.917	2.915
.2	2.855	2.855	2.859	2.852	2.861	2.857	2.857	2.853	2.858	2.863	2.857
.3	2.793	2.786	2.792	2.795	2.792	2.797	2.795	2.797	2.792	2.798	2.794
.4	2.726	2.730	2.720	2.723	2.719	2.723	2.715	2.725	2.719	2.726	2.722
.5	2.638	2.636	2.632	2.633	2.643	2.638	2.637	2.635	2.636	2.638	2.637
.6	2.556	2.543	2.552	2.550	2.553	2.540	2.549	2.547	2.543	2.544	2.548
.7	2.447	2.446	2.438	2.439	2.433	2.440	2.437	2.447	2.441	2.435	2.440
.8	2.318	2.314	2.318	2.316	2.310	2.321	2.314	2.307	2.311	2.318	2.315
.9	2.175	2.173	2.160	2.175	2.159	2.178	2.167	2.169	2.172	2.178	2.171
1	2.004	2.004	2.004	1.999	2.009	1.996	2.003	1.994	1.993	2.004	2.001
Mean	2.543	2.540	2.539	2.539	2.540	2.541	2.539	2.539	2.538	2.542	2.540

Table 2.8 Simulation 4A: Rate/1000 That Moving-Average Parameter's Absolute t-stat > 1.96 by *d* values of X and Y

d(Y)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.2	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.3	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.4	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.5	1000	999	1000	1000	999	999	1000	1000	999	999	9995
.6	995	992	997	998	993	991	996	996	993	992	9943
.7	948	947	952	933	941	944	943	939	931	929	9407
.8	692	686	701	705	689	707	688	670	687	697	6922
.9	274	279	241	281	250	280	255	262	275	281	2678
1	59	71	59	66	64	78	59	76	73	61	666
Totals	7968	7974	7950	7983	7936	7999	7941	7943	7958	7959	79611

Table 2.9 Simulation 4A: Rate/1000 That Moving-Average Parameter was Invertible by *d* values of X and Y

	d(X)										
d(Y)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	702	703	684	663	699	691	686	693	698	721	6940
.2	825	825	839	807	834	820	821	815	849	821	8256
.3	928	944	941	943	942	935	931	937	962	918	9381
.4	988	986	983	986	982	988	989	979	989	984	9854
.5	999	998	999	1000	999	999	998	998	997	999	9986
.6	999	1000	1000	1000	1000	1000	999	1000	1000	1000	9998
.7	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.8	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.9	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
1	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
Totals	9441	9456	9446	9399	9486	9433	9424	9422	9495	9443	94415

Table 2.10 Simulation 4A: Type I Errors by *d* Values of X and Y

d value for dep. variable, Y	*d* value for independent variable - X .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	**153**	**161**	**164**	**183**	**163**	**164**	**156**	**136**	**136**	**137**	1553
.2	**136**	**142**	**128**	**138**	**134**	**116**	**139**	**117**	**99**	**120**	1269
.3	**102**	**97**	**100**	**96**	**90**	**96**	**103**	**102**	**91**	**90**	967
.4	**70**	**84**	**73**	**66**	**74**	**79**	**76**	**81**	**76**	**65**	744
.5	62	**68**	59	62	54	59	52	60	58	58	592
.6	**65**	61	53	61	52	62	52	**66**	**68**	**70**	610
.7	**68**	62	60	53	56	55	**64**	37	54	55	564
.8	54	47	**67**	54	50	59	52	**66**	49	54	552
.9	48	59	59	51	56	50	60	53	61	48	545
1	58	62	**71**	52	46	49	62	59	55	46	560
Totals	816	843	834	816	775	789	816	777	747	743	7956

Bold figures are statistically distinguishable from 50 (.05).

Table 2.11 Simulation 4A: Average R-Square by *d* values of X and Y

d(Y)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.431	0.432	0.431	0.430	0.431	0.433	0.433	0.430	0.429	0.432	0.431
.2	0.371	0.370	0.369	0.368	0.372	0.371	0.372	0.373	0.369	0.373	0.371
.3	0.304	0.301	0.301	0.303	0.301	0.304	0.305	0.303	0.299	0.307	0.303
.4	0.239	0.242	0.238	0.237	0.235	0.239	0.238	0.240	0.237	0.240	0.238
.5	0.179	0.177	0.176	0.177	0.180	0.179	0.178	0.178	0.179	0.180	0.178
.6	0.130	0.125	0.128	0.128	0.128	0.124	0.127	0.127	0.125	0.126	0.127
.7	0.085	0.084	0.082	0.082	0.080	0.082	0.081	0.083	0.083	0.081	0.082
.8	0.047	0.047	0.048	0.047	0.046	0.048	0.047	0.046	0.046	0.047	0.047
.9	0.024	0.024	0.022	0.023	0.023	0.024	0.023	0.023	0.023	0.023	0.023
1	0.014	0.014	0.014	0.013	0.013	0.013	0.014	0.014	0.014	0.013	0.014
Mean	0.182	0.182	0.181	0.181	0.181	0.182	0.182	0.182	0.180	0.182	0.182

Table 2.12 Simulation 6: Type I Errors by *d* Values of X and Y

d value for dep. variable, Y	*d* value for independent variable - X										
	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	**97**	**101**	**105**	**89**	**81**	**77**	**68**	**85**	58	52	813
.2	**109**	**97**	**89**	**84**	**101**	**83**	**73**	**74**	55	60	825
.3	**97**	**91**	**109**	**83**	**67**	**87**	**87**	63	62	55	801
.4	**95**	**87**	**86**	**98**	**98**	**76**	**69**	**74**	56	46	785
.5	**88**	**70**	**88**	**99**	**79**	**74**	**79**	55	**66**	53	751
.6	**91**	**72**	**75**	**72**	**85**	**66**	62	**66**	**69**	57	715
.7	**82**	**72**	**78**	**79**	**83**	57	56	57	51	50	665
.8	**69**	**68**	**64**	**74**	54	**68**	**67**	**68**	49	49	630
.9	**69**	61	**72**	**67**	**68**	**67**	53	50	**66**	43	616
1	44	48	58	**70**	51	51	60	48	43	41	514
Totals	841	767	824	815	767	706	674	640	575	506	7115

Bold figures are statistically distinguishable from 50 (.05).

Table 2.13 Simulation 6: Standard Errors by *d* Values of X and Y

d(Y)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.083	0.086	0.090	0.095	0.099	0.102	0.105	0.108	0.110	0.112	0.099
.2	0.078	0.083	0.086	0.090	0.094	0.098	0.100	0.103	0.105	0.107	0.094
.3	0.075	0.079	0.083	0.086	0.090	0.093	0.096	0.099	0.101	0.101	0.090
.4	0.072	0.075	0.079	0.082	0.086	0.089	0.092	0.094	0.096	0.098	0.086
.5	0.070	0.073	0.076	0.079	0.083	0.085	0.089	0.091	0.092	0.093	0.083
.6	0.067	0.070	0.073	0.077	0.079	0.083	0.085	0.088	0.089	0.090	0.080
.7	0.065	0.068	0.071	0.074	0.077	0.080	0.083	0.085	0.086	0.087	0.078
.8	0.063	0.066	0.070	0.072	0.075	0.078	0.081	0.082	0.084	0.085	0.076
.9	0.062	0.065	0.067	0.071	0.074	0.077	0.079	0.081	0.082	0.083	0.074
1	0.061	0.064	0.067	0.070	0.073	0.076	0.079	0.080	0.082	0.082	0.073
Mean	0.070	0.073	0.076	0.080	0.083	0.086	0.089	0.091	0.093	0.094	0.084

Table 2.14 Simulation 6: Absolute X-Coefficients by *d* Values of X and Y

d(Y)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.079	0.080	0.085	0.089	0.089	0.090	0.091	0.093	0.094	0.091	0.088
.2	0.077	0.078	0.081	0.081	0.086	0.085	0.086	0.089	0.089	0.088	0.084
.3	0.071	0.072	0.077	0.079	0.080	0.084	0.087	0.082	0.082	0.083	0.080
.4	0.067	0.070	0.073	0.076	0.078	0.078	0.080	0.082	0.079	0.078	0.076
.5	0.065	0.063	0.069	0.072	0.072	0.074	0.076	0.076	0.077	0.072	0.072
.6	0.062	0.061	0.066	0.067	0.069	0.068	0.072	0.073	0.074	0.071	0.068
.7	0.058	0.058	0.061	0.065	0.066	0.067	0.069	0.069	0.069	0.069	0.065
.8	0.054	0.056	0.061	0.061	0.062	0.067	0.068	0.069	0.067	0.068	0.063
.9	0.051	0.054	0.059	0.059	0.061	0.065	0.066	0.065	0.068	0.064	0.061
1	0.047	0.051	0.054	0.058	0.057	0.061	0.064	0.063	0.064	0.063	0.058
Mean	0.063	0.064	0.069	0.071	0.072	0.074	0.076	0.076	0.076	0.075	0.072

Table 2.15 Simulation 6A: Rate/1000 That Moving-Average Parameter's Absolute t-stat > 1.96 by *d* values of X and Y

	d(X)										
d(Y)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.2	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.3	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.4	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.5	1000	1000	1000	1000	1000	1000	1000	999	1000	1000	9999
.6	984	993	991	994	998	995	993	996	996	993	9933
.7	938	929	938	945	944	929	930	941	947	935	9376
.8	657	668	694	699	657	695	691	691	688	695	6835
.9	277	253	267	262	261	249	262	283	258	283	2655
1	48	72	67	84	62	71	61	44	47	60	616
Totals	7904	7915	7957	7984	7922	7939	7937	7954	7936	7966	79414

Table 2.16 Simulation 6A: Average Value of Standard Errors for Moving-Average Parameters by *d* values of X and Y

	d(X)										
d(Y)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.035	0.034	0.034	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
.2	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041	0.041
.3	0.052	0.051	0.051	0.051	0.050	0.051	0.051	0.051	0.051	0.051	0.051
.4	0.061	0.062	0.062	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061
.5	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069	0.069
.6	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075
.7	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
.8	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081
.9	0.082	0.082	0.082	0.082	0.082	0.083	0.083	0.082	0.083	0.083	0.082
1	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
Mean	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066

Table 2.17 Simulation 6A: Average Absolute Value of Moving-Average Parameter's Coefficient by *d* values of X and Y

	d(X)										
d(Y)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.934	0.943	0.943	0.936	0.942	0.943	0.939	0.942	0.948	0.953	0.942
.2	0.882	0.882	0.883	0.882	0.883	0.882	0.883	0.883	0.889	0.886	0.883
.3	0.771	0.780	0.785	0.785	0.789	0.783	0.783	0.783	0.788	0.785	0.783
.4	0.664	0.659	0.661	0.663	0.664	0.662	0.663	0.668	0.667	0.670	0.664
.5	0.543	0.538	0.541	0.546	0.541	0.542	0.548	0.549	0.550	0.552	0.545
.6	0.421	0.422	0.421	0.426	0.426	0.429	0.427	0.425	0.431	0.431	0.426
.7	0.311	0.311	0.312	0.314	0.314	0.317	0.312	0.317	0.316	0.318	0.314
.8	0.205	0.207	0.209	0.210	0.200	0.210	0.211	0.207	0.211	0.207	0.208
.9	0.115	0.115	0.117	0.115	0.118	0.111	0.116	0.119	0.115	0.118	0.116
1	0.066	0.068	0.070	0.073	0.069	0.069	0.069	0.063	0.066	0.069	0.068
Mean	0.491	0.492	0.494	0.495	0.495	0.495	0.495	0.496	0.498	0.499	0.495

Table 2.18 Simulation 6A: Moving-Average Parameter's Average Absolute t-stat by *d* values of X and Y

	d(X)										
d(Y)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	29.36	30.29	30.47	29.26	29.91	29.36	29.48	29.65	30.01	30.15	29.80
.2	24.23	24.49	24.59	24.54	24.21	24.23	24.10	24.37	24.61	24.02	24.34
.3	16.35	16.99	17.22	17.15	17.45	16.98	17.32	16.92	17.06	16.90	17.03
.4	11.45	11.35	11.36	11.60	11.60	11.61	11.43	11.62	11.85	11.79	11.57
.5	8.14	8.03	8.03	8.16	8.08	8.07	8.23	8.20	8.27	8.43	8.16
.6	5.74	5.73	5.73	5.81	5.80	5.84	5.83	5.78	5.88	5.88	5.80
.7	4.00	4.01	4.02	4.03	4.05	4.09	4.01	4.10	4.06	4.11	4.05
.8	2.55	2.58	2.60	2.62	2.48	2.61	2.63	2.58	2.63	2.58	2.59
.9	1.40	1.40	1.43	1.40	1.44	1.35	1.42	1.45	1.40	1.44	1.41
1	0.80	0.83	0.85	0.88	0.83	0.84	0.84	0.77	0.80	0.83	0.83
Mean	10.40	10.57	10.63	10.55	10.59	10.50	10.53	10.54	10.66	10.61	10.56

Table 2.19 Simulation 6A: Average R^2 by *d* values of X and Y

d(Y)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.427	0.431	0.430	0.429	0.433	0.430	0.428	0.429	0.434	0.435	0.430
.2	0.371	0.370	0.368	0.370	0.371	0.372	0.372	0.371	0.372	0.371	0.371
.3	0.300	0.300	0.306	0.303	0.305	0.303	0.302	0.301	0.304	0.301	0.303
.4	0.238	0.235	0.239	0.238	0.237	0.235	0.238	0.238	0.235	0.238	0.237
.5	0.181	0.176	0.177	0.178	0.178	0.176	0.180	0.179	0.180	0.181	0.179
.6	0.125	0.124	0.125	0.126	0.127	0.126	0.126	0.125	0.128	0.129	0.126
.7	0.081	0.081	0.082	0.082	0.083	0.083	0.080	0.083	0.081	0.082	0.082
.8	0.046	0.047	0.047	0.048	0.045	0.047	0.048	0.046	0.047	0.046	0.047
.9	0.023	0.023	0.024	0.023	0.024	0.022	0.023	0.023	0.023	0.023	0.023
1	0.013	0.014	0.014	0.015	0.014	0.014	0.014	0.013	0.013	0.013	0.014
Mean	0.181	0.180	0.181	0.181	0.181	0.181	0.181	0.181	0.182	0.182	0.181

Table 2.20 Simulation 6A: Type I Errors by *d* Values of X and Y

d value for dep. variable, Y	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
	d value for independent variable - X										
.1	**117**	**136**	**120**	**108**	**131**	**134**	**132**	**144**	**140**	**139**	1301
.2	**103**	**99**	**92**	**113**	**96**	**123**	**140**	**116**	**137**	**122**	1141
.3	**71**	**65**	**72**	**73**	**75**	**96**	**104**	**80**	**92**	**92**	820
.4	56	**69**	**67**	**74**	**72**	**76**	**85**	**87**	**73**	**81**	740
.5	62	47	60	63	**67**	54	**67**	57	**72**	**67**	616
.6	53	49	48	54	62	59	52	63	**69**	**65**	574
.7	56	52	**64**	63	56	56	60	63	54	57	581
.8	51	48	57	61	49	56	61	59	53	51	546
.9	62	55	59	63	**66**	63	49	47	**67**	45	576
1	46	54	56	**68**	48	54	57	44	42	46	515
Totals	677	674	695	740	722	771	807	760	799	765	7410

Bold figures are statistically distinguishable from 50 (.05).

Table 2.21 Simulation 6B: Type I Errors by *d* Values of X and Y

d value for dep. variable, Y	*d* value for independent variable - X .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	**67**	59	**73**	**68**	**67**	62	**68**	**64**	58	46	632
.2	**71**	56	**65**	49	**75**	**72**	51	63	53	55	610
.3	**79**	61	**73**	**64**	**70**	60	**76**	60	63	56	662
.4	53	**67**	**64**	**67**	**72**	**67**	57	63	58	45	613
.5	59	50	63	**66**	57	56	**70**	39	52	62	574
.6	63	47	60	54	**71**	56	46	61	59	52	569
.7	**68**	56	57	62	60	51	48	59	48	43	552
.8	55	47	55	61	49	55	57	61	47	48	535
.9	48	55	55	58	63	59	45	49	63	44	539
1	44	53	51	**68**	49	52	53	46	39	45	500
Totals	607	551	616	617	633	590	571	565	540	496	5786

Bold figures are statistically distinguishable from 50 (.05).

Table 2.22 Simulation 6B: Type I Errors for Autoregressive Parameter by *d* Values of X and Y

d value for dep. variable, Y	*d* value for independent variable - X										
	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Total
.1	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.2	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	10000
.3	999	1000	1000	1000	999	1000	1000	1000	1000	1000	9998
.4	1000	997	1000	999	999	999	1000	999	999	999	9991
.5	988	991	994	995	989	996	997	993	990	994	9927
.6	950	953	945	957	942	961	956	952	961	963	9540
.7	791	807	835	833	814	816	820	814	848	836	8214
.8	506	526	521	556	501	535	536	525	541	531	5278
.9	194	170	200	194	198	172	165	192	192	197	1874
1	35	51	57	67	54	48	42	43	41	45	483
Totals	7463	7495	7552	7601	7496	7527	7516	7518	7572	7565	75305

Bold figures are statistically distinguishable from 50 (.05).

Table 2.23 Simulations 6C, 6D, 6, 6E, &6F: Standard Errors by *d* Values of Y and Sample Size

d value for dep. Y	SAMPLE SIZE				
	T=50	T=100	T=150	T=200	T=500
.1	0.176	0.122	0.099	0.085	0.054
.2	0.167	0.116	0.094	0.082	0.051
.3	0.160	0.111	0.090	0.078	0.049
.4	0.153	0.106	0.086	0.075	0.047
.5	0.147	0.102	0.083	0.072	0.045
.6	0.141	0.099	0.080	0.069	0.044
.7	0.137	0.095	0.078	0.067	0.042
.8	0.134	0.093	0.076	0.065	0.041
.9	0.131	0.091	0.074	0.064	0.040
1	0.129	0.090	0.073	0.063	0.040
Mean	0.147	0.103	0.084	0.072	0.045

Table 3.1 Summary Statistics for Control Simulation

Variable	Obs	Mean	Std. Dev.	Min	Max
X-Coefficient	100,000	-0.0002	0.0830	-0.3276	0.3415
X-Standard Error	100,000	0.0824	0.0068	0.0570	0.1162
X-t-statistic	100,000	-0.0017	1.0101	-3.9551	4.3147
W-Coefficient	100,000	-0.0002	0.0826	-0.3863	0.3291
W-Standard Error	100,000	0.0824	0.0068	0.0569	0.1171
W-t-statistic	100,000	-0.0029	1.0056	-4.6031	4.2262
Durbin-Watson	100,000	1.9998	0.1617	1.2924	2.6345
R-Square	100,000	0.0135	0.0133	0.0000	0.1385
Absolute X-t-stat	100,000	0.8057	0.6092	0.0000	4.3147
Absolute W-t-stat	100,000	0.8005	0.6086	0.0000	4.6031
X-type I errors	100,000	0.0529	0.2238	0	1
W-type I errors	100,000	0.0519	0.2218	0	1

Table 3.2 Simulation 1: Type I Errors for X by *d* Values of X and W
N=1,000,000*

d value for indep variable, X	*d* value for independent variable - W										
	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	**547**	541	**555**	502	501	537	524	491	522	522	5242
.2	495	504	521	531	493	499	**543**	524	510	504	5124
.3	**567**	523	531	479	**575**	**548**	517	531	500	532	5303
.4	**546**	509	492	537	**563**	522	523	527	511	**566**	5296
.5	510	535	527	503	525	513	520	486	512	**548**	5179
.6	532	510	532	510	527	**547**	513	499	525	516	5211
.7	523	519	510	517	522	529	**553**	488	526	497	5184
.8	538	518	493	542	476	525	511	530	483	498	5114
.9	529	**548**	536	530	479	494	**551**	527	531	531	5256
1	485	507	521	534	532	524	510	503	540	512	5168
Totals	5272	5214	5218	5185	5193	5238	5265	5106	5160	5226	52077

Bold figures are statistically distinguishable from 500 (.05).

* Note that each cell is based on 10,000 regressions, 1,000 for each *d* value of Y. This is the case for every simulation table that follows.

Table 3.3 Simulation 1: Type I Errors for W by *d* Values of X and W
N=1,000,000

d value for indep variable, X	*d* value for independent variable - W										
	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	487	**552**	524	540	499	517	509	532	502	546	5208
.2	513	497	511	512	537	490	522	518	496	**554**	5150
.3	527	542	515	505	520	541	515	531	503	513	5212
.4	511	**549**	509	519	518	537	535	540	522	496	5236
.5	**558**	542	507	489	502	**550**	549	500	529	521	5247
.6	512	520	524	490	498	511	**551**	500	553	**548**	5207
.7	528	525	497	519	517	466	484	534	**548**	527	5145
.8	526	504	534	527	524	541	533	510	533	495	5227
.9	512	523	540	529	520	537	**558**	513	503	504	5239
1	502	507	530	525	530	476	514	523	**561**	523	5191
Totals	5176	5261	5191	5155	5165	5166	5270	5201	5250	5227	52062

Bold figures are statistically distinguishable from 500 (.05).

Table 3.4 Simulation 1: Average Durbin-Watson Value by *d* values of X and W

d(X)	d(W) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	1.995	1.997	1.994	1.993	1.996	1.996	1.997	1.995	1.998	1.995	1.995
.2	1.995	1.998	1.994	1.996	1.996	1.994	1.998	1.996	1.995	1.995	1.996
.3	1.993	1.996	1.997	1.994	1.993	1.994	1.996	1.998	1.993	1.996	1.995
.4	1.997	1.996	1.995	1.996	1.997	1.997	1.996	1.996	1.994	1.995	1.996
.5	1.995	1.991	1.995	1.998	1.994	1.993	1.990	1.995	1.993	1.996	1.994
.6	1.994	1.996	1.992	1.993	1.995	1.994	1.995	1.994	1.997	1.995	1.995
.7	1.995	1.994	1.997	1.994	1.995	1.996	1.998	1.993	1.998	1.996	1.996
.8	1.994	1.997	1.994	1.996	1.994	1.996	1.993	1.996	1.994	1.995	1.995
.9	1.995	1.998	1.995	1.997	1.996	1.998	1.997	1.995	2.000	1.996	1.997
1	1.995	1.996	1.993	1.995	1.993	1.998	1.997	1.994	1.992	1.996	1.995
Mean	1.995	1.996	1.995	1.995	1.995	1.995	1.996	1.995	1.995	1.995	1.995

Table 3.5 Simulation 1: Average Value of X’s Coefficient by *d* values of X and W

d(X)	d(W) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	-0.001	0.000	-0.001	0.000	0.001	0.000	0.000	-0.001	-0.001	0.001	0.000
.2	-0.002	0.000	0.000	0.001	0.000	0.001	-0.001	0.000	0.000	0.000	0.000
.3	-0.001	-0.001	0.000	0.001	0.001	-0.001	0.000	0.001	0.001	0.001	0.000
.4	0.001	0.000	0.000	0.000	0.000	0.000	-0.001	0.002	0.001	0.000	0.000
.5	0.001	0.001	0.000	0.000	-0.001	0.000	0.001	0.001	0.002	0.000	0.000
.6	-0.001	0.000	-0.001	-0.002	0.000	-0.001	-0.001	0.001	-0.001	0.000	-0.001
.7	0.000	0.000	-0.001	0.001	0.000	0.000	0.001	0.000	0.000	-0.002	0.000
.8	0.001	0.000	-0.001	-0.001	0.000	-0.001	-0.001	-0.001	-0.001	0.001	0.000
.9	0.000	-0.001	-0.001	0.001	-0.001	0.000	0.002	0.001	0.000	0.000	0.000
1	-0.001	0.001	0.000	-0.001	-0.002	0.000	0.001	0.000	-0.001	0.001	0.000
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 3.6 Simulation 1: Average Standard Error for X by *d* values of X and W

	d(W)										
d(X)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.2	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.3	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.4	0.082	0.082	0.082	0.082	0.083	0.082	0.083	0.082	0.082	0.082	0.082
.5	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.6	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.7	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.8	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.9	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
1	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
Mean	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083

Table 3.7 Simulation 2: Average Absolute Value of X's Coefficient by *d* values of X and W

	d(W)										
d(X)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.066	0.066	0.067	0.066	0.066	0.066	0.066	0.066	0.065	0.066	0.066
.2	0.065	0.065	0.065	0.065	0.064	0.064	0.066	0.064	0.065	0.065	0.065
.3	0.062	0.062	0.062	0.062	0.063	0.062	0.061	0.063	0.062	0.063	0.062
.4	0.058	0.058	0.057	0.058	0.059	0.059	0.058	0.059	0.059	0.059	0.058
.5	0.052	0.052	0.052	0.051	0.052	0.052	0.052	0.053	0.052	0.053	0.052
.6	0.044	0.044	0.044	0.045	0.046	0.045	0.045	0.046	0.047	0.046	0.045
.7	0.037	0.037	0.037	0.037	0.037	0.038	0.039	0.039	0.039	0.040	0.038
.8	0.029	0.029	0.030	0.030	0.031	0.031	0.031	0.031	0.032	0.032	0.031
.9	0.023	0.023	0.023	0.023	0.023	0.024	0.024	0.024	0.025	0.025	0.024
1	0.017	0.017	0.017	0.018	0.017	0.018	0.018	0.019	0.019	0.020	0.018
Mean	0.045	0.045	0.045	0.045	0.046	0.046	0.046	0.046	0.047	0.047	0.046

Table 3.8 Simulation 2: Average Standard Error for X by *d* values of X and W

d(X)	d(W) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.082	0.082	0.083	0.082	0.082	0.083	0.083	0.082	0.083	0.083	0.082
.2	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081	0.081
.3	0.077	0.077	0.077	0.077	0.077	0.078	0.078	0.078	0.078	0.078	0.078
.4	0.072	0.072	0.072	0.072	0.072	0.072	0.073	0.073	0.073	0.073	0.072
.5	0.064	0.064	0.064	0.064	0.065	0.065	0.065	0.066	0.066	0.066	0.065
.6	0.055	0.055	0.055	0.056	0.056	0.056	0.057	0.057	0.058	0.058	0.056
.7	0.045	0.046	0.046	0.046	0.046	0.047	0.048	0.048	0.048	0.049	0.047
.8	0.036	0.036	0.036	0.037	0.037	0.038	0.038	0.039	0.040	0.040	0.038
.9	0.028	0.028	0.028	0.028	0.029	0.029	0.030	0.030	0.031	0.031	0.029
1	0.021	0.021	0.021	0.021	0.021	0.022	0.022	0.023	0.023	0.024	0.022
Mean	0.056	0.056	0.056	0.056	0.057	0.057	0.057	0.058	0.058	0.058	0.057

Table 3.9 Simulation 3: Type I Errors for W by *d* Values of X and W
N=1,000,000

d value for indep variable, W	*d* value for independent variable - X: .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	494	489	527	492	523	511	**543**	541	537	505	5162
.2	**549**	536	505	504	532	530	**550**	492	523	513	5234
.3	519	507	517	**559**	504	**546**	521	**545**	**543**	**550**	5311
.4	521	526	**591**	540	540	**558**	540	**549**	**556**	**554**	5475
.5	**546**	**544**	**560**	**565**	**544**	**550**	**552**	541	**551**	**566**	5519
.6	528	**607**	**583**	**575**	**551**	**567**	526	508	**547**	**572**	5564
.7	**543**	530	**554**	**556**	**584**	**561**	**575**	**627**	**554**	521	5605
.8	**545**	540	**584**	**635**	**596**	**573**	**581**	**566**	537	**600**	5757
.9	**570**	**643**	**585**	**612**	**569**	**558**	**568**	**574**	**574**	**591**	5844
1	**587**	**588**	**587**	**574**	**589**	**604**	**642**	**567**	**616**	**639**	5993
Total	5402	5510	5593	5612	5532	5558	5598	5510	5538	5611	55464

Bold figures are statistically distinguishable from 500 (.05).

Table 3.10 Simulation 3: Average Absolute Value of W’s Coefficient by *d* values of X and W

	d(X)										
d(W)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.066	0.065	0.066	0.066	0.067	0.067	0.067	0.066	0.067	0.066	0.066
.2	0.065	0.065	0.064	0.065	0.066	0.066	0.065	0.065	0.065	0.065	0.065
.3	0.062	0.061	0.062	0.062	0.062	0.063	0.063	0.064	0.063	0.063	0.062
.4	0.057	0.058	0.058	0.058	0.059	0.059	0.058	0.059	0.059	0.059	0.059
.5	0.052	0.052	0.052	0.053	0.053	0.052	0.053	0.054	0.054	0.055	0.053
.6	0.045	0.045	0.046	0.045	0.045	0.046	0.046	0.047	0.048	0.048	0.046
.7	0.037	0.037	0.037	0.038	0.038	0.039	0.039	0.040	0.040	0.040	0.039
.8	0.029	0.030	0.030	0.031	0.031	0.031	0.032	0.032	0.032	0.033	0.031
.9	0.023	0.024	0.023	0.024	0.024	0.024	0.025	0.025	0.026	0.026	0.024
1	0.017	0.017	0.017	0.018	0.018	0.018	0.019	0.019	0.020	0.020	0.018
Mean	0.045	0.045	0.046	0.046	0.046	0.047	0.047	0.047	0.047	0.048	0.046

Table 3.11 Simulation 3: Average Standard Error for W by *d* values of X and W

d(W)	d(X) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
.2	0.081	0.081	0.081	0.081	0.081	0.081	0.082	0.082	0.082	0.082	0.081
.3	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.078	0.079	0.078
.4	0.072	0.072	0.072	0.072	0.072	0.073	0.073	0.073	0.073	0.074	0.073
.5	0.064	0.065	0.065	0.065	0.065	0.066	0.066	0.066	0.067	0.067	0.065
.6	0.056	0.055	0.056	0.056	0.056	0.057	0.057	0.058	0.058	0.058	0.057
.7	0.046	0.046	0.046	0.046	0.047	0.047	0.048	0.049	0.049	0.050	0.047
.8	0.036	0.037	0.037	0.037	0.037	0.038	0.039	0.039	0.040	0.040	0.038
.9	0.028	0.028	0.028	0.029	0.029	0.029	0.030	0.031	0.031	0.032	0.030
1	0.021	0.021	0.021	0.021	0.022	0.022	0.022	0.023	0.024	0.024	0.022
Mean	0.056	0.057	0.057	0.057	0.057	0.057	0.058	0.058	0.058	0.059	0.057

Table 3.12 Simulation 4: Average Durbin-Watson Value by *d* values of X and W

	d(W)										
d(X)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	1.986	1.984	1.987	1.987	1.986	1.987	1.987	1.987	1.989	1.992	1.987
.2	1.984	1.983	1.983	1.986	1.990	1.988	1.989	1.988	1.987	1.992	1.987
.3	1.984	1.986	1.985	1.987	1.987	1.985	1.987	1.990	1.991	1.993	1.988
.4	1.986	1.986	1.988	1.985	1.987	1.986	1.989	1.992	1.989	1.991	1.988
.5	1.983	1.987	1.986	1.986	1.988	1.989	1.988	1.993	1.991	1.992	1.988
.6	1.988	1.989	1.988	1.987	1.990	1.987	1.989	1.991	1.995	1.994	1.990
.7	1.987	1.983	1.986	1.990	1.988	1.990	1.991	1.988	1.993	1.990	1.989
.8	1.986	1.988	1.988	1.989	1.988	1.990	1.995	1.992	1.995	1.995	1.991
.9	1.988	1.990	1.989	1.992	1.990	1.991	1.993	1.993	1.994	1.995	1.992
1	1.990	1.991	1.991	1.992	1.991	1.993	1.995	1.996	1.997	1.997	1.993
Mean	1.986	1.987	1.987	1.988	1.989	1.989	1.990	1.991	1.992	1.993	1.989

Table 3.13 Simulation 4: Average Absolute Value of X's Coefficient by *d* Values of X and W

	d(W)										
d(X)	.1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.049	0.049	0.049	0.049	0.049	0.049	0.050	0.049	0.050	0.049	0.049
.2	0.051	0.052	0.052	0.052	0.051	0.050	0.051	0.052	0.051	0.051	0.051
.3	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.053	0.053	0.054
.4	0.057	0.056	0.057	0.056	0.057	0.057	0.057	0.056	0.056	0.056	0.056
.5	0.059	0.058	0.058	0.058	0.058	0.058	0.059	0.059	0.059	0.058	0.059
.6	0.061	0.061	0.060	0.060	0.060	0.061	0.061	0.061	0.061	0.060	0.061
.7	0.063	0.062	0.063	0.063	0.063	0.062	0.062	0.062	0.063	0.063	0.063
.8	0.064	0.064	0.065	0.064	0.064	0.065	0.064	0.064	0.065	0.064	0.064
.9	0.065	0.065	0.065	0.066	0.067	0.066	0.066	0.066	0.065	0.065	0.066
1	0.066	0.066	0.066	0.066	0.066	0.066	0.065	0.066	0.066	0.067	0.066
Mean	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059

Table 3.14 Simulation 4: Average Standard Error for X by *d* Values of X and W

d(X)	d(W) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	0.062	0.062	0.061	0.061	0.062	0.062	0.062	0.061	0.061	0.061	0.061
.2	0.065	0.064	0.065	0.064	0.064	0.065	0.065	0.065	0.065	0.064	0.064
.3	0.068	0.067	0.068	0.067	0.068	0.068	0.068	0.067	0.067	0.067	0.067
.4	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070
.5	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073	0.073
.6	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
.7	0.078	0.079	0.079	0.078	0.078	0.079	0.078	0.078	0.078	0.078	0.078
.8	0.080	0.081	0.081	0.081	0.081	0.081	0.081	0.080	0.081	0.080	0.081
.9	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082
1	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
Mean	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074

Table 3.15 Simulation 5: Type I Errors for W by *d* Values of X and W
N=1,000,000

d value for indep variable, W	*d* value for independent variable - X .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Total
1											
.1	**847**	**844**	**776**	**838**	**870**	**873**	**849**	**832**	**803**	**853**	8385
.2	**818**	**828**	**878**	**837**	**830**	**809**	**784**	**793**	**843**	**804**	8224
.3	**761**	**787**	**809**	**781**	**794**	**819**	**836**	**850**	**771**	**748**	7956
.4	**791**	**761**	**757**	**765**	**819**	**768**	**801**	**741**	**778**	**784**	7765
.5	**741**	**786**	**746**	**740**	**774**	**768**	**750**	**768**	**763**	**712**	7548
.6	**735**	**721**	**706**	**686**	**713**	**687**	**701**	**698**	**724**	**740**	7111
.7	**663**	**671**	**694**	**747**	**647**	**651**	**685**	**701**	**687**	**645**	6791
.8	**629**	**627**	**651**	**598**	**640**	**637**	**648**	**669**	**637**	**652**	6388
.9	**565**	**568**	**580**	**567**	**553**	**589**	**580**	538	**550**	**569**	5659
1	**549**	507	511	520	530	506	506	**558**	539	527	5253
Total	7099	7100	7108	7079	7170	7107	7140	7148	7095	7034	71080

Bold figures are statistically distinguishable from 500 (.05).

Table 3.16 Simulation 5: Type I Errors for W by *d* Values of X and W where *d*(Y)=0.7, N=100,000

d value for dep. variable, W	*d* value for independent variable - X .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Totals
.1	**73**	**81**	**74**	**69**	**88**	**93**	**83**	**76**	**74**	**77**	788
.2	**80**	**78**	**90**	**76**	**65**	**78**	**75**	**75**	**85**	**72**	774
.3	**64**	60	**80**	**89**	**89**	**66**	**79**	**89**	**80**	**64**	760
.4	**64**	**78**	**64**	**85**	**71**	**82**	**89**	57	**80**	**76**	746
.5	**68**	**67**	**79**	**71**	**81**	**89**	63	**79**	62	58	717
.6	**79**	**66**	**87**	60	**78**	60	60	**75**	55	**70**	690
.7	**67**	**65**	**74**	**75**	63	51	54	**73**	52	**73**	647
.8	54	60	**64**	58	**74**	**68**	**67**	**64**	57	**64**	630
.9	63	56	47	48	55	50	59	47	50	55	530
1	59	61	39	**70**	56	47	49	52	49	63	545
Total	671	672	698	701	720	684	678	687	644	672	6827

Bold figures are statistically distinguishable from 500 (.05).

Table 3.17 Simulation 5: Average Durbin-Watson Value by *d* values of X and W

d(X)	d(W) .1	.2	.3	.4	.5	.6	.7	.8	.9	1	Mean
.1	2.533	2.530	2.533	2.531	2.530	2.532	2.533	2.528	2.532	2.534	2.532
.2	2.530	2.530	2.533	2.530	2.530	2.533	2.531	2.534	2.531	2.534	2.532
.3	2.532	2.530	2.531	2.533	2.531	2.533	2.533	2.531	2.534	2.536	2.532
.4	2.531	2.530	2.534	2.531	2.531	2.531	2.533	2.532	2.533	2.536	2.532
.5	2.531	2.532	2.533	2.533	2.532	2.532	2.534	2.533	2.534	2.534	2.533
.6	2.532	2.532	2.531	2.534	2.531	2.533	2.532	2.534	2.535	2.537	2.533
.7	2.528	2.534	2.532	2.535	2.532	2.533	2.535	2.536	2.536	2.534	2.534
.8	2.532	2.530	2.532	2.532	2.533	2.535	2.533	2.535	2.533	2.534	2.533
.9	2.533	2.534	2.532	2.532	2.535	2.534	2.535	2.534	2.535	2.535	2.534
1	2.535	2.532	2.535	2.533	2.534	2.534	2.532	2.535	2.533	2.535	2.534
Mean	2.532	2.531	2.532	2.532	2.532	2.533	2.533	2.533	2.534	2.535	2.533

Table 4.1 Dickey-Fuller and Aumented Dickey-Fuller Results, N=210

	Dickey-Fuller	Augmented Dickey-Fuller[a]
Critical Values → Variable Name ⇓	α= .10: -2.57 α= .05: -2.88 α= .01: -3.46	α= .10: -2.57 α= .05: -2.88 α= .01: -3.46
Conservative	-2.596*	-1.957
PM Approval	-2.693*	-2.472
Pers. Expect.	-4.154***	-2.727*
Pers. Retrospec.	-3.026**	-2.137
Nat. Expect.	-5.908***	-3.359**
Nat. Retrospec.	-2.993**	-1.933

[a] taken to three lags.
* reject the null hypothesis of unit-root process at the .10 level.
** reject the null hypothesis of unit-root process at the .05 level.
*** reject the null hypothesis of unit-root process at the .01 level.

Table 4.2 Variance Ratio Test Results, N=210

Differencing Interval (k) →	R(2)	R(4)[a]	R(8)[a]	R(16)	R(32)
Critical Values[b]→ Variable Name ⇓	α=.05: 1.157 α=.10: 1.122	**1.328** **1.254**	**1.609** **1.465**	2.170 1.891	3.578 2.909
Governing Support.	1.175**	**1.409****	**1.646****	1.788	2.532
PM Approval	1.066	**1.120**	**1.349**	1.309	2.021
Personal Expects.	1.219**	**1.735****	**2.538****	2.869**	4.227**
Personal Retrospecs.	1.420**	**1.778****	**2.152****	2.016*	2.526
National Expects.	1.291**	**2.142****	**3.248****	4.200**	6.056**
National Retrospecs.	1.139*	**1.527****	**1.771****	1.784	2.014

* reject null hypothesis of Random walk with drift at the .10 level in a one-sided test.
** reject null hypothesis of Random walk with drift at the .05 level in a one-sided test.
[a] The recommended differencing intervals are K=4 or k=8 (Diebold, 1989:38).
[b] Critical values are given in Diebold (1989:33-35).

Table 4.3 KPSS Test for Strong Mixing with Intercept (η_μ), N=210

Lag Trunc. Parameter → Variable ⇓	l=0	l=2	l=4[a]	l=6	l=8
Governing Support.	7.736***	2.738***	**1.708*** **	1.265***	1.018***
PM Approval	4.782***	1.700***	**1.074*** **	0.805***	0.654**
Personal Expects.	1.853***	0.707**	**0.458* **	0.347*	0.284
Personal Retrospecs.	1.968***	0.705**	**0.441* **	0.327	0.263
National Expects.	0.686**	0.294	**0.203**	0.159	0.134
National Retrospecs.	1.383***	0.498**	**0.313**	0.233	0.188

Critical Values: p<.1: .347; p<.05: .463; p<.01: .739.
* reject the null hypothesis of stationary, strong mixing process at the .10 level.
** reject the null hypothesis of stationary, strong mixing process at the .05 level.
*** reject the null hypothesis of stationary, strong mixing process at the .01 level.
[a] Recommended lag trucation (l) is given by Kwiatkowski, Phillips, Schmidt, and Shin (1992:169-73); l = integer[$4(T/100)^{.25}$] = 4 for these series.

Table 4.4 KPSS Test for Strong Mixing with Intercept and Linear Time Trend (η_τ), N=210

Lag Trunc. Parameter → Variable ⇓	l=0	l=2	l=4[a]	l=6	l=8
Governing Support.	1.894***	0.686***	**0.434*** **	0.326***	0.266***
PM Approval	1.195***	0.430***	**0.275*** **	0.208**	0.170**
Personal Expects.	1.740***	0.663***	**0.430*** **	0.326***	0.267***
Personal Retrospecs.	1.700***	0.610***	**0.382*** **	0.283***	0.228***
National Expects.	0.478***	0.206**	**0.142* **	0.111	0.094
National Retrospecs.	1.452***	0.522***	**0.329*** **	0.244***	0.197**

Critical Values: p<.1: .119; p<.05: .146; p<.01: .216.
* reject the null hypothesis of stationary, strong mixing process at the .10 level.
** reject the null hypothesis of stationary, strong mixing process at the .05 level.
*** reject the null hypothesis of stationary, strong mixing process at the .01 level.
[a] Recommended lag trucation (l) is given by Kwiatkowski, Phillips, Schmidt, and Shin (1992:169-73); l = integer[$4(T/100)^{.25}$] = 4 for these series.

Table 4.5 Summary of Stationarity Tests,* N=210

	D-F/AD-F	VR Test[a]	KPSS η_μ[b]	KPSS η_τ[b]	Prognosis
H(0) → Variable ⇓	d=1	d=1	d=0	d=0 with trend	
Governing Support.	d=1	Reject d=1	Reject d=0	No trend	$0<d\leq 1$
PM Approval	d=1	d=1	Reject d=0	No trend	$0<d\leq 1$
Personal Expects.	Reject d=1	Reject d=1	d=0	No trend	$0\leq d<1$
Personal Retrospecs.	Reject d=1	Reject d=1	d=0	No trend	$0\leq d<1$
National Expects.	Reject d=1	Reject d=1	d=0	Trend Stationary	$0\leq d<1$
National Retrospecs.	Reject d=1	Reject d=1	d=0	No trend	$0\leq d<1$

* All at .05 level of significance.
[a] Differencing interval R(4), R(8).
[b] Lag truncation parameter=4.

Table 4.6 Estimates of *d* Based on Robinson's and Sowell's Procedures, N=210

VARIABLE	Robinson's *d* estimate (s.e.)	Sowell's *d* estimate (s.e.)	T-stat[a] ($d \neq 0$)	T-stat[a] ($d \neq 1$)
Conservative Party Support	0.85 (0.059)	0.82 (0.058)	14.32**	-2.53*
Prime Ministerial Approval	0.96 (0.059)	0.91 (0.060)	16.18**	-0.67
Personal Economic Expectations	0.70 (0.059)	0.72 (0.059)	11.80**	-5.06**
Personal Economic Retrospections	0.84 (0.059)	0.77 (0.051)	14.16**	-2.70**
National Economic Expectations	0.63 (0.059)	0.61 (0.060)	10.62**	-6.24**
National Economic Retrospections	0.83 (0.059)	0.83 (0.057)	13.99**	-2.86**

* - p<.05
** - p<.01
[a] based on Robinson's procedure.

Table 4.7 Governing Party Support - Multivariate ARFIMA Models, N=209

	Pers. Expect	Pers. Retro.	Nat. Expect.	Nat. Retro.
Constant	-0.123 (0.133)	-0.132 (0.132)	-0.149 (0.133)	-0.136 (0.133)
Pers. Expect.	0.055 (0.028)*			
Pers. Retro.		0.068 (0.032)*		
Nat. Expect.			0.015 (0.013)	
Nat. Retro				0.012 (0.014)
PM Sat. (Frac. Diff.)	0.362 (0.037)**	0.367 (0.037)**	0.367 (0.038)**	0.371 (0.038)**
ECM (1) (Frac. Diff.)	-0.282 (0.058)**	-0.283 (0.058)**	-0.293 (0.058)**	-0.291 (0.058)**
Election 83	3.357 (1.326)**	3.594 (1.312)**	3.600 (1.325)**	3.681 (1.323)**
Election 92	4.305 (1.295)**	4.378 (1.293)**	4.335 (1.303)**	4.398 (1.307)**
Falklands	6.407 (1.868)**	6.634 (1.862)**	6.555 (1.877)**	6.475 (1.875)**
Poll Tax	-3.155 (1.312)**	-3.875 (1.315)**	-3.365 (1.313)**	-3.468 (1.312)**
Major	5.778 (1.861)**	5.685 (1.861)**	6.026 (1.867)**	6.000 (1.871)**
Events	1.634 (0.290)**	1.591 (0.288)**	1.612 (0.292)**	1.612 (0.294)**
R-Square	.596	.597	.591	.590
Sum of Residuals^2	663.5	661.5	671.7	673.7
Durbin-Watson	1.90	1.91	1.89	1.89
Q (36-0)	30.6	26.9	27.4	27.4

Coefficients are shown - standard errors are in parenthesis.
* significant at .05 level - one tail.   ** significant at .01 level - one tail.

Table 4.8 Personal Expectations Models - Various Specifications, N=209

	ARFIMA Both Sides	ARIMA[a]	ARFIMA ECM level-form[b]	ARFIMA One-Step
Constant	-0.123 (0.133)	0.041 (0.137)	-0.035 (0.132)	1.320 (0.596)*
Pers. Expect.	0.055 (0.028)*	0.060 (0.027)*	0.056 (0.029)*	0.056 (0.029)*
Governing Support (t-1)				-0.177 (0.040)**
PM Sat. (t-1)				0.127 (0.031)**
PM Sat.	0.362 (0.037)**	0.377 (0.038)**	0.365 (0.038)**	0.366 (0.039)**
ECM (1)	-0.282 (0.058)**	-.228 (0.042)**	-0.177 (0.04)**	
Election 83	3.357 (1.326)**	2.766 (1.373)*	3.109 (1.332)*	3.070 (1.341)*
Election 92	4.305 (1.295)**	4.612 (1.356)**	4.290 (1.305)**	4.302 (1.309)**
Falklands	6.407 (1.868)**	6.030 (1.954)**	6.349 (1.883)**	6.339 (1.888)**
Poll Tax	-3.155 (1.312)**	-3.038 (1.371)*	-3.015 (1.322)*	-3.021 (1.326)*
Major	5.778 (1.861)**	4.464 (1.955)*	5.137 (1.885)**	5.165 (1.891)**
Events	1.634 (0.290)**	1.588 (0.302)**	1.714 (0.292)**	1.703 (0.295)**
R-Square	.596	.570	.587	.588
Sum of Residuals^2	663.5	731.4	677.5	677.2
Durbin-Watson	1.90	2.23	2.11	2.12
Q(36-0)	30.6	41.3	36.1	35.7

Coefficients are shown - standard errors are in parenthesis.
[a] Conservative support, PM approval, Pers. Expectations are differenced - ECM is level-form.
[b] Same as column 1 except for ECM which is left in level-form.
* significant at .05 level - one tail.   ** significant at .01 level - one tail.

Table 4.9 The J-test for Encompassing - Personal Expectations vs. Retrospections

Personal Retrospections ξ Personal Expectations

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.030	0.151	-0.201	0.841
PR Y-Hats	**0.711**	**0.553**	**1.287***	**0.199**
PE	0.034	0.033	1.034	0.303
PMSAT - F. differenced	0.098	0.209	0.470	0.639
ECM(1) - F. differenced	-0.077	0.169	-0.046	0.649
Election 83	0.850	2.355	0.361	0.718
Election 92	1.235	2.713	0.455	0.650
Falklands War	1.776	4.052	0.438	0.662
Poll Tax	-0.810	2.244	-0.361	0.719
Major begins	1.568	3.761	0.417	0.677
Events	0.492	0.933	0.527	0.599

Personal Expectations ξ Personal Retrospections

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.048	0.155	-0.313	0.755
PE Y-Hats	**0.614**	**0.594**	**1.034****	**0.302**
PR	0.048	0.037	1.287	0.199
PMSAT - F. differenced	0.137	0.226	0.606	0.545
ECM(1) - F. differenced	-0.106	0.181	-0.583	0.561
Election 83	1.346	2.539	0.530	0.597
Election 92	1.707	2.890	0.591	0.555
Falklands War	2.563	4.356	0.588	0.557
Poll Tax	-1.630	2.539	-0.642	0.522
Major begins	2.067	3.965	0.521	0.603
Events	0.621	0.982	0.632	0.528

* The personal retropections model does not encompass the personal expectations model.
** The personal expectations model does not encompass the personal retrospections model.

Table 4.10 The J-test for Encompassing - Personal Expectations vs. Retrospections
One-Step Error Correction Model

Personal Retrospections ξ Personal Expectations

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	0.420	0.975	0.431	0.667
PR Y-Hats	**0.678**	**0.582**	**1.165***	**0.246**
PE	0.037	0.033	1.116	0.266
PMSAT - F. differenced	0.111	0.223	0.498	0.619
Conservative support(1)	-0.540	0.113	-0.476	0.635
PMSAT(1)	0.038	0.082	0.465	0.643
Election 83	0.872	2.315	0.377	0.707
Election 92	1.376	2.832	0.486	0.628
Falklands War	1.967	4.201	0.468	0.640
Poll Tax	-0.869	2.273	-0.382	0.703
Major begins	1.567	3.621	0.433	0.666
Events	0.569	1.017	0.560	0.576

Personal Expectations ξ Personal Retrospections

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	0.409	0.973	0.421	0.674
PE Y-Hats	**0.659**	**0.591**	**1.116****	**0.266**
PR	0.043	0.037	1.165	0.246
PMSAT - F. differenced	0.121	0.228	0.534	0.594
Conservative support(1)	-0.057	0.115	-0.499	0.618
PMSAT(1)	0.036	0.091	0.396	0.721
Election 83	1.088	2.389	0.456	0.643
Election 92	1.508	2.884	0.523	0.602
Falklands War	2.248	4.311	0.521	0.603
Poll Tax	-1.405	2.470	-0.569	0.570
Major begins	1.628	3.649	0.446	0.656
Events	0.570	1.017	0.560	0.576

* The personal retropections model does not encompass the personal expectations model.
** The personal expectations model does not encompass the personal retrospections model.

Table 4.11 The J-test for Encompassing - Model with Fractionally Differenced Error Correction Mechanism vs. Model with Level-Form Error Correction Mechanism

Fractionally Differenced ECM ξ Level-Form ECM

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.008	0.130	-0.062	0.951
ECM FRACDIFF Y-Hats	**0.712**	**0.251**	**2.832***	**0.005**
PE	0.013	0.032	0.391	0.696
PMSAT - F. differenced	0.113	0.096	0.177	0.241
ECM(1)	-0.095	0.049	-1.938	0.054
Election 83	1.050	1.497	0.701	0.484
Election 92	1.215	1.680	0.723	0.471
Falklands War	1.747	2.463	0.710	0.479
Poll Tax	-0.845	1.509	-0.560	0.576
Major begins	1.281	2.299	0.557	0.578
Events	0.502	0.516	0.973	0.332

Level-Form ECM ξ Fractionally Differenced ECM

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.078	0.134	-0.587	0.558
ECM LEVEL-FORM Y-Hats	**0.539**	**0.278**	**1.939****	**0.054**
PE	0.022	0.033	0.653	0.515
PMSAT - F. differenced	0.174	0.104	1.676	0.095
ECMDF(1)	-0.201	0.071	-2.822	0.005
Election 83	1.766	1.551	1.138	0.256
Election 92	1.966	1.763	1.115	0.266
Falklands War	2.889	2.595	1.113	0.267
Poll Tax	-1.465	1.567	-0.935	0.351
Major begins	2.622	2.463	1.065	0.288
Events	0.741	0.543	1.364	0.174

* Fractionally differenced ECM encompasses level-form ECM (.01 level).
** Level-form ECM does not encompass fractionally differenced ECM (.05 level).

Table 5.1 Dickey-Fuller and Aumented Dickey-Fuller Results, N=240

	Dickey-Fuller	Augmented Dickey-Fuller[a]
Critical Values → Variable Name ⇓	α= .10: -2.57 α= .05: -2.88 α= .01: -3.46	α= .10: -2.57 α= .05: -2.88 α= .01: -3.46
Presidential Approval	-3.447**	-3.528***
Personal Expectations	-4.832***	-3.474***
Personal Retrospections	-3.479***	-2.270
National Expectations	-4.019***	-3.007**
National Retrospections	-1.823	-2.350

[a] taken to three lags.
* reject the null hypothesis of unit-root process at the .10 level.
** reject the null hypothesis of unit-root process at the .05 level.
*** reject the null hypothesis of unit-root process at the .01 level.

Table 5.2 Variance Ratio Test Results, N=240

Differencing Interval (k) →	R(2)	R(4)[a]	R(8)[a]	R(16)	R(32)
Critical Values[b]→ Variable Name ⇓	α=.05: 1.157 α=.10: 1.122	**1.328** **1.254**	**1.609** **1.465**	2.170 1.891	3.578 2.909
Presidential Approval	0.937	**0.959**	**1.217**	1.666	2.379
Personal Expects.	1.583**	**2.084****	**3.984****	5.770**	8.150**
Personal Retrospecs.	1.634**	**2.128****	**3.438****	3.924**	4.554**
National Expects.	1.283**	**1.636****	**2.139****	3.152**	4.155**
National Retrospecs.	0.848	**0.670**	**0.775**	0.781	0.980

* reject null hypothesis of Random walk with drift at the .10 level in a one-sided test.
** reject null hypothesis of Random walk with drift at the .05 level in a one-sided test.
[a] The recommended differencing intervals are K=4 or k=8 (Diebold, 1989:38).
[b] Critical values are given in Diebold (1989:33-35).

Table 5.3 KPSS Test for Strong Mixing with Intercept (η_μ), N=240

Lag Trunc. Parameter → Variable ⇓	l=0	l=2	l=4[a]	l=6	l=8
Presidential Approval	2.176***	0.796***	**0.519****	0.400*	0.333
Personal Expects.	3.853***	2.329***	**1.510*****	1.146***	0.933***
Personal Retrospecs.	5.025***	1.820***	**1.137*****	0.837***	0.667**
National Expects.	2.743***	1.025***	**0.659****	0.500**	0.412*
National Retrospecs.	2.761***	0.955***	**0.595****	0.442*	0.357*

Critical Values: p<.1: .347; p<.05: .463; p<.01: .739.
* reject the null hypothesis of stationary, strong mixing process at the .10 level.
** reject the null hypothesis of stationary, strong mixing process at the .05 level.
*** reject the null hypothesis of stationary, strong mixing process at the .01 level.
[a] Recommended lag trucation (l) is given by Kwiatkowski, Phillips, Schmidt, and Shin (1992:169-73); l = integer[4(T/100)$^{.25}$] = 4 for these series.

Table 5.4 KPSS Test for Strong Mixing with Intercept and Linear Time Trend (η_τ), N=240

Lag Trunc. Parameter → Variable ⇓	l=0	l=2	l=4[a]	l=6	l=8
Presidential Approval	1.539***	0.563***	**0.367*****	0.283***	0.236***
Personal Expects.	2.250***	0.898***	**0.592*****	0.454***	0.372***
Personal Retrospecs.	2.766***	1.014***	**0.637*****	0.469***	0.374***
National Expects.	1.854***	0.695***	**0.446*****	0.338***	0.279***
National Retrospecs.	1.742***	0.602***	**0.376*****	0.279***	0.225***

Critical Values: p<.1: .119; p<.05: .146; p<.01: .216.
* reject the null hypothesis of stationary, strong mixing process at the .10 level.
** reject the null hypothesis of stationary, strong mixing process at the .05 level.
*** reject the null hypothesis of stationary, strong mixing process at the .01 level.
[a] Recommended lag trucation (l) is given by Kwiatkowski, Phillips, Schmidt, and Shin (1992:169-73); l = integer[$4(T/100)^{.25}$] = 4 for these series.

Table 5.5 Summary of Stationarity Tests,* N=240

	D-F/AD-F	VR Test[a]	KPSS η_{μ}[b]	KPSS η_{τ}[b]	Prognosis
H(0) → Variable ⇓	*d*=1	*d*=1	*d*=0	*d*=0 with trend	
Presidential Approval	Reject *d*=1	*d*=1	Reject *d*=0	No trend	$0<d\leq 1$
Personal Expects.	Reject *d*=1	Reject *d*=1	Reject *d*=0	No trend	$0<d<1$
Personal Retrospecs.	Reject *d*=1	Reject *d*=1	Reject *d*=0	No trend	$0<d<1$
National Expects.	Reject *d*=1	Reject *d*=1	Reject *d*=0	No trend	$0<d<1$
National Retrospecs.	*d*=1	*d*=1	Reject *d*=0	No trend	*d* = 1

* All at .05 level of significance.
[a] Differencing interval R(4), R(8).
[b] Lag truncation parameter=4.

Table 5.6 Estimates of *d* Based on Robinson's and Sowell's Procedures, N=240

VARIABLE	Robinson's *d* estimate (s.e.)	Sowell's *d* estimate (s.e.)	T-stat[a] ($d \neq 0$)	T-stat[a] ($d \neq 1$)
Presidential Approval	0.94 (0.056)	0.97 (0.060)	16.71**	-1.07
Personal Economic Expectations	0.66 (0.056)	0.60 (0.050)	11.73**	-6.04**
Personal Economic Retrospections	0.75 (0.056)	0.64 (0.045)	13.33**	-5.64**
National Economic Expectations	0.73 (0.056)	0.72 (0.052)	12.98**	-4.80**
National Economic Retrospections	0.89 (0.056)	0.89 (0.060)	14.96**	-1.98*

* p<.05
** p<.01
[a] based on Robinson's procedure.

Table 5.7 Stationarity Tests for the Residuals of Cointegrating Regressions with Presidential Approval (*d*=.94 (s.e.=.056)), N=240

Independent Var.	Residuals' *d* Value	Dickey-Fuller Test Statistic*	Regression Coeffiecient (s.e.)	Series' *d* Value (s.e.)
Personal Economic Expectations	0.91 (0.056)	-3.54***	0.44^{+} (0.062)	0.66 (0.056)
Personal Economic Retrospections	0.88 (0.056)	-3.77***	0.34^{+} (0.049)	0.75 (0.056)
National Economic Expectations	0.91 (0.056)	-3.29**	0.23^{+} (0.037)	0.73 (0.056)
National Economic Retrospections	0.94 (0.056)	-3.42**	0.07^{+} (0.019)	0.89 (0.056)

* critical values are α= .10: -2.57, α= .05: -2.88, and α= .01: -3.46.
** reject the null hypothesis of unit-root process at the .05 level.
*** reject the null hypothesis of unit-root process at the .01 level.
$^{+}$ statistically significant at the .01 level.

Table 5.8 Presidential Approval - Multivariate ARFIMA Models, N=239

	Pers. Expect.	Pers. Retro.	Nat. Expect.	Nat. Retro.
Constant	-0.297 (0.22)	-0.264 (0.22)	-0.291 (0.21)	-0.259 (0.21)
Pers. Expect.	0.122 (0.05)*			
Pers. Retro.		0.042 (0.04)		
Nat. Expect.			0.121 (0.03)**	
Nat. Retro.				0.081 (0.02)**
Iran Rescue	10.246 (3.32)**	10.170 (3.36)**	9.817 (3.24)**	10.757 (3.27)**
Iran Resc. (1)	13.288 (3.32)**	13.825 (3.36)**	14.223 (3.24)**	13.536 (3.27)**
Hostages	-8.432 (2.35)**	-7.978 (2.37)**	-7.876 (2.29)**	-8.107 (2.31)**
Reagan	12.022 (2.71)**	12.693 (2.73)**	11.832 (2.64)**	12.396 (2.66)**
Assassination	7.498 (2.36)**	7.301 (2.39)**	7.453 (2.31)**	7.439 (2.33)**
Iran-Contra	-11.64 (2.71)**	-12.32 (2.73)**	-11.15 (2.70)**	-12.17 (2.66)**
Bush	4.580 (1.71)**	4.047 (1.74)*	4.824 (1.67)**	4.965 (1.69)**
Tienanmen	10.543 (2.41)**	10.435 (2.44)**	10.752 (2.35)**	10.286 (2.38)**
Desert Storm	23.139 (3.31)**	23.812 (3.36)**	21.912 (3.25)**	23.159 (3.26)**
Events	2.463 (0.36)**	2.413 (0.37)**	2.538 (0.35)**	2.417 (0.36)**
R-Square	0.478	0.466	.503	0.493
Sum of Resids^2	2486.1	2543.5	2368.8	2414.7
Durbin-Watson	1.87	1.85	1.95	1.94
Q(36-0)	39.6	36.7	47.2	40.2

Coefficients are shown - standard errors are in parenthesis.
* significant at .05 level - one tail test. ** significant at .01 level - one tail test.

Table 5.9 National Prospections Models - Various Specifications, N=239

	All Variables Fractionally Differenced	Interventions Wholly Differenced	All Variables Wholly Differenced
Constant	-0.291 (0.21)	-0.221 (0.21)	-0.185 (0.21)
Nat. Expect.	0.121 (0.03)**	0.124 (0.03)**	0.088 (0.023)**
Iran Rescue	9.817 (3.24)**	9.873 (3.27)**	10.046 (3.28)**
Iran Resc. (1)	14.223 (3.24)**	14.877 (3.27)**	14.236 (3.28)**
Hostages	-7.876 (2.29)**	-7.261 (2.31)**	-7.794 (2.31)**
Reagan	11.832 (2.64)**	11.725 (2.67)**	12.039 (2.68)**
Assassination	7.453 (2.31)**	7.269 (2.30)**	7.112 (2.31)**
Iran-Contra	-11.15 (2.70)**	-11.10 (2.68)**	-11.21 (2.69)**
Bush	4.824 (1.67)**	4.765 (1.64)**	4.839 (1.64)**
Tienanmen	10.752 (2.35)**	10.416 (2.31)**	10.719 (2.31)**
Desert Storm	21.912 (3.25)**	22.152 (3.28)**	22.381 (3.30)**
Events	2.538 (0.35)**	2.411 (0.35)**	2.487 (0.35)**
R-Square	.503	.494	.491
Sum of Resids^2	2368.8	2411.7	2423.8
Durbin-Watson	1.95	1.95	2.01
Q(36-0)	47.2	46.8	43.4

Coefficients are shown - standard errors are in parenthesis.
* significant at .05 level - one tail test. ** significant at .01 level - one tail test.

Table 5.10 The J-test for Encompassing - National Expectations vs. Personal Expectations

National Expectations ξ Personal Expectations

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.045	0.220	-0.204	0.838
Nat. Expects. Y-Hats	**0.913**	**0.228**	**4.010***	**0.000**
Pers. Expects.	0.063	0.049	1.273	0.204
Iran Rescue	0.928	3.966	0.234	0.815
Iran Rescue (1)	1.008	4.441	0.227	0.821
Hostages	-0.900	2.951	-0.305	0.761
Reagan	0.766	3.843	0.200	0.842
Assassination	0.669	2.851	0.235	0.815
Iran-Contra	-0.737	3.781	-0.195	0.846
Bush	0.536	1.940	0.277	0.782
Tienanmen	0.978	3.338	0.293	0.770
Desert Storm	1.875	6.199	0.302	0.763
Events	0.222	0.660	0.337	0.736

Personal Expectations ξ National Expectations

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.155	0.237	-0.655	0.513
Pers. Expects. Y-Hats	**0.524**	**0.409**	**1.281****	**0.201**
Nat. Expects.	0.108	0.030	3.595	0.000
Iran Rescue	4.529	5.244	0.864	0.389
Iran Rescue (1)	7.018	6.489	1.082	0.281
Hostages	-3.679	3.994	-0.921	0.358
Reagan	5.267	5.757	0.917	0.360
Assassination	3.546	3.821	0.928	0.354
Iran-Contra	-4.827	5.597	-0.862	0.389
Bush	2.535	2.445	1.037	0.301
Tienanmen	5.267	4.885	1.078	0.282
Desert Storm	9.780	10.012	0.977	0.330
Events	1.250	1.067	1.169	0.244

* The national expectations encompasses the personal expectations model (.01 level).
** The personal expectations model does not encompass the national expectations model (.05 level).

Table 5.11 The J-Test for Encompassing - National Expectations vs. National Retrospections

National Expectations ξ National Retrospections

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.055	0.219	-0.250	0.803
Nat. Expects. Y-Hats	**0.797**	**0.250**	**3.193***	**0.002**
Nat. Retrospects.	0.041	0.025	1.631	0.104
Iran Rescue	2.360	4.149	0.569	0.570
Iran Rescue (1)	2.712	4.666	0.581	0.562
Hostages	-1.662	3.034	-0.548	0.584
Reagan	2.425	4.069	0.596	0.552
Assassination	1.529	2.949	0.518	0.605
Iran-Contra	-2.430	4.014	-0.605	0.546
Bush	1.222	2.032	0.601	0.548
Tienanmen	2.049	3.476	0.590	0.556
Desert Storm	4.599	6.636	0.693	0.489
Events	0.481	0.700	0.688	0.492

National Retrospections ξ National Expectations

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.139	0.227	-0.613	0.540
Nat. Retros. Y-Hats	**0.565**	**0.313**	**1.805****	**0.072**
Nat. Expectations	0.091	0.033	2.776	0.006
Iran Rescue	4.161	4.495	0.926	0.356
Iran Rescue (1)	6.375	5.413	1.178	0.240
Hostages	-3.373	3.378	-0.999	0.319
Reagan	4.876	4.664	1.046	0.297
Assassination	3.241	3.272	0.991	0.323
Iran-Contra	-4.485	4.535	-0.989	0.324
Bush	2.280	2.180	1.046	0.297
Tienanmen	4.790	4.049	1.183	0.238
Desert Storm	9.038	7.832	1.154	0.250
Events	1.134	0.854	1.329	0.185

* The national expectations encompasses the national retrospections model (.01 level).
** The national retrospections model does not encompass the national expectations model (.05 level).

Table 5.12 The J-test for Encompassing - Wholly Differenced Interventions vs. Fractionally Differenced Interventions - National Expectations Models

Wholly Differenced ξ Fractionally Differenced

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	-0.844	0.382	-2.208	0.028
Wholly Diff. Y-Hats	**-1.887**	**1.088**	**-1.734***	**0.084**
Nat. Expectations	0.348	0.134	2.592	0.010
Iran Rescue	28.480	11.237	2.534	0.012
Iran Rescue (1)	41.078	15.822	2.596	0.010
Hostages	-21.949	8.431	-2.603	0.010
Reagan	33.237	12.623	2.633	0.009
Assassination	20.978	8.131	2.580	0.011
Iran-Contra	-31.637	12.110	-2.612	0.010
Bush	14.044	5.572	2.520	0.012
Tienanmen	30.971	11.895	2.604	0.010
Desert Storm	63.684	24.309	2.620	0.009
Events	7.216	2.721	2.652	0.009

Fractionally Differenced ξ Wholly Differenced

Variable	Coeff.	Std. E.	T-Stat	Signif.
constant	0.428	0.315	1.359	0.176
Fraction. Diff. Y-Hats	**2.973**	**1.077**	**2.760****	**0.006**
Nat. Expectations	-0.245	0.137	-1.792	0.074
Iran Rescue	-19.084	10.976	-1.739	0.083
Iran Rescue (1)	-29.003	16.223	-1.788	0.075
Hostages	15.484	8.550	1.811	0.071
Reagan	-24.334	13.329	-1.826	0.069
Assassination	-15.096	8.417	-1.734	0.074
Iran-Contra	22.513	12.462	1.807	0.072
Bush	-9.209	5.315	-1.733	0.085
Tienanmen	-20.619	11.474	-1.797	0.074
Desert Storm	-42.686	23.717	-1.800	0.073
Events	-4.917	2.677	-1.836	0.068

* The wholly differenced intervention model does not encompass the fractionally differenced intervention model (.05 level).
** The fractionally differenced intervention model encompasses the wholly differenced intervention model (.01 level).

FIGURES

Figure 1.1: A Stationary Series, d=0

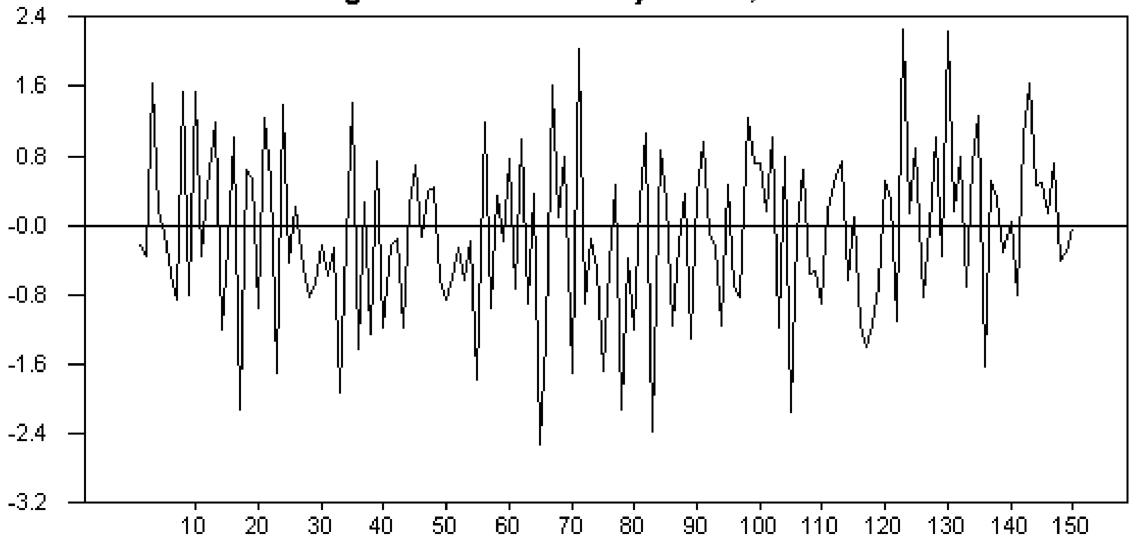


Figure 1.2: A Fractionally Integrated Series, d=0.25

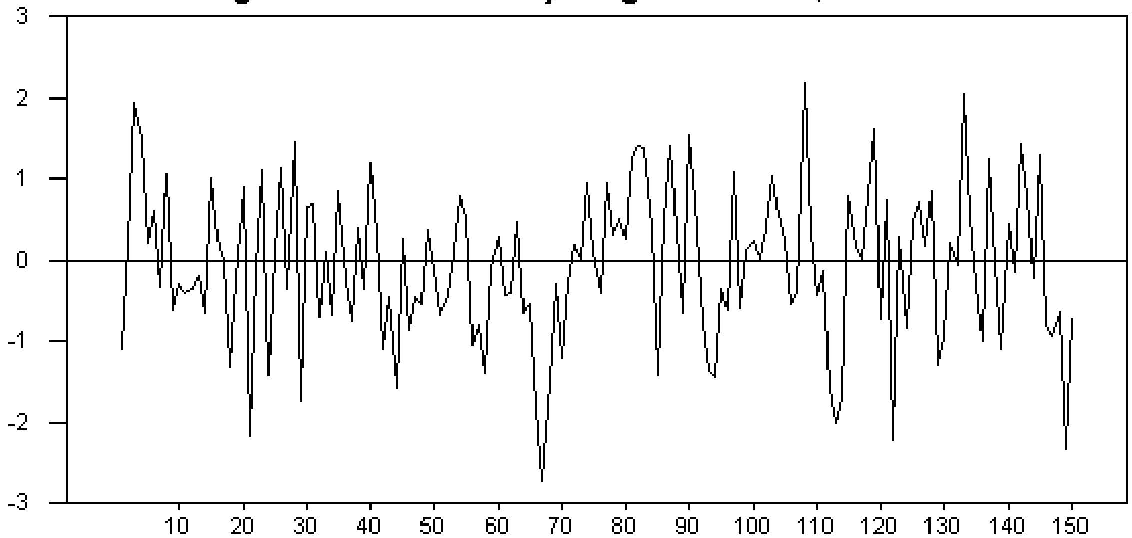


Figure 1.3: A Fractionally Integrated Series, d=0.5

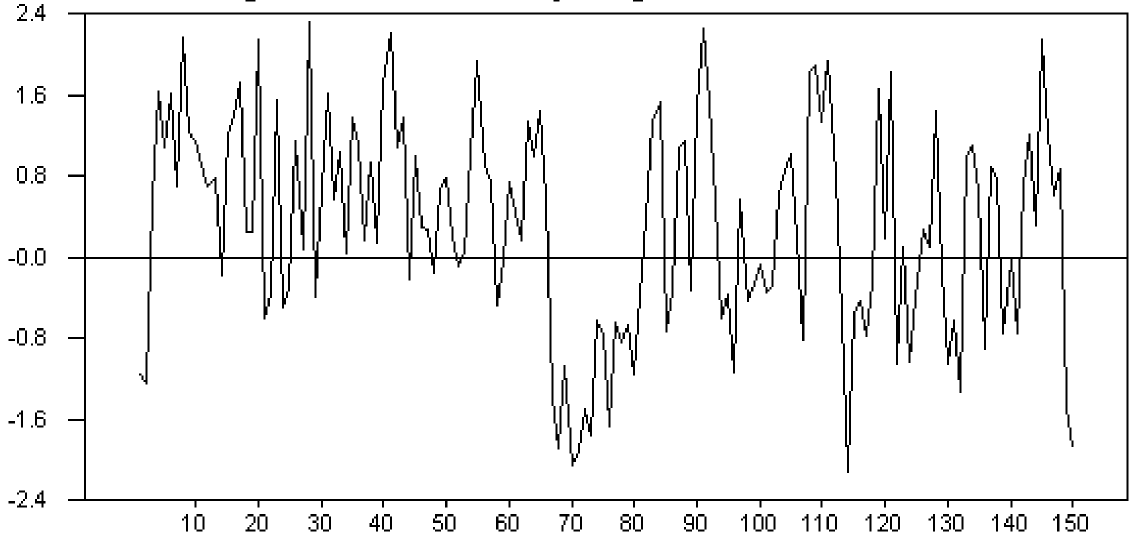


Figure 1.4: A Fractionally Integrated Series, d=0.75

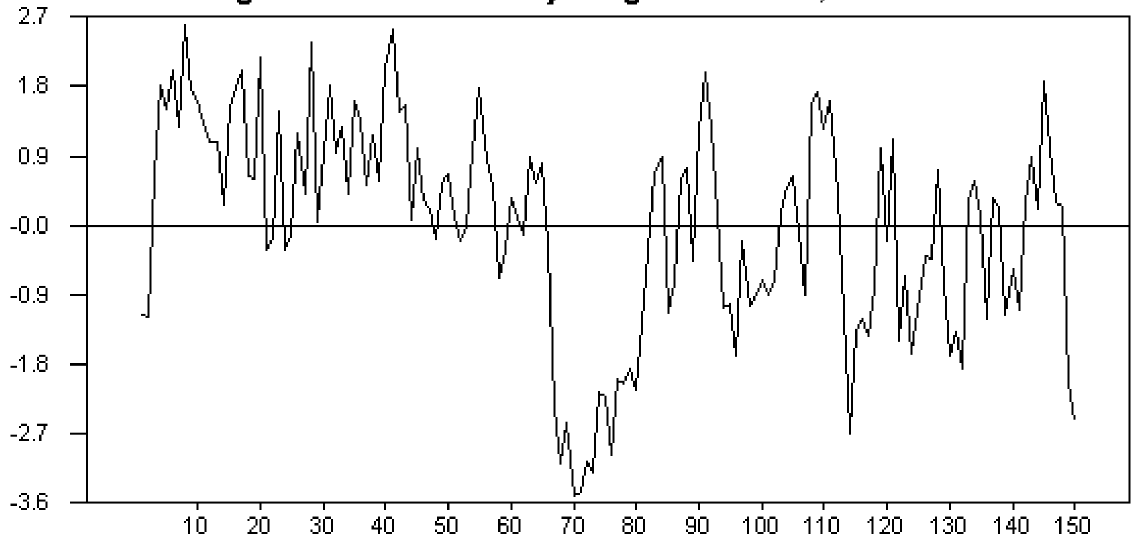
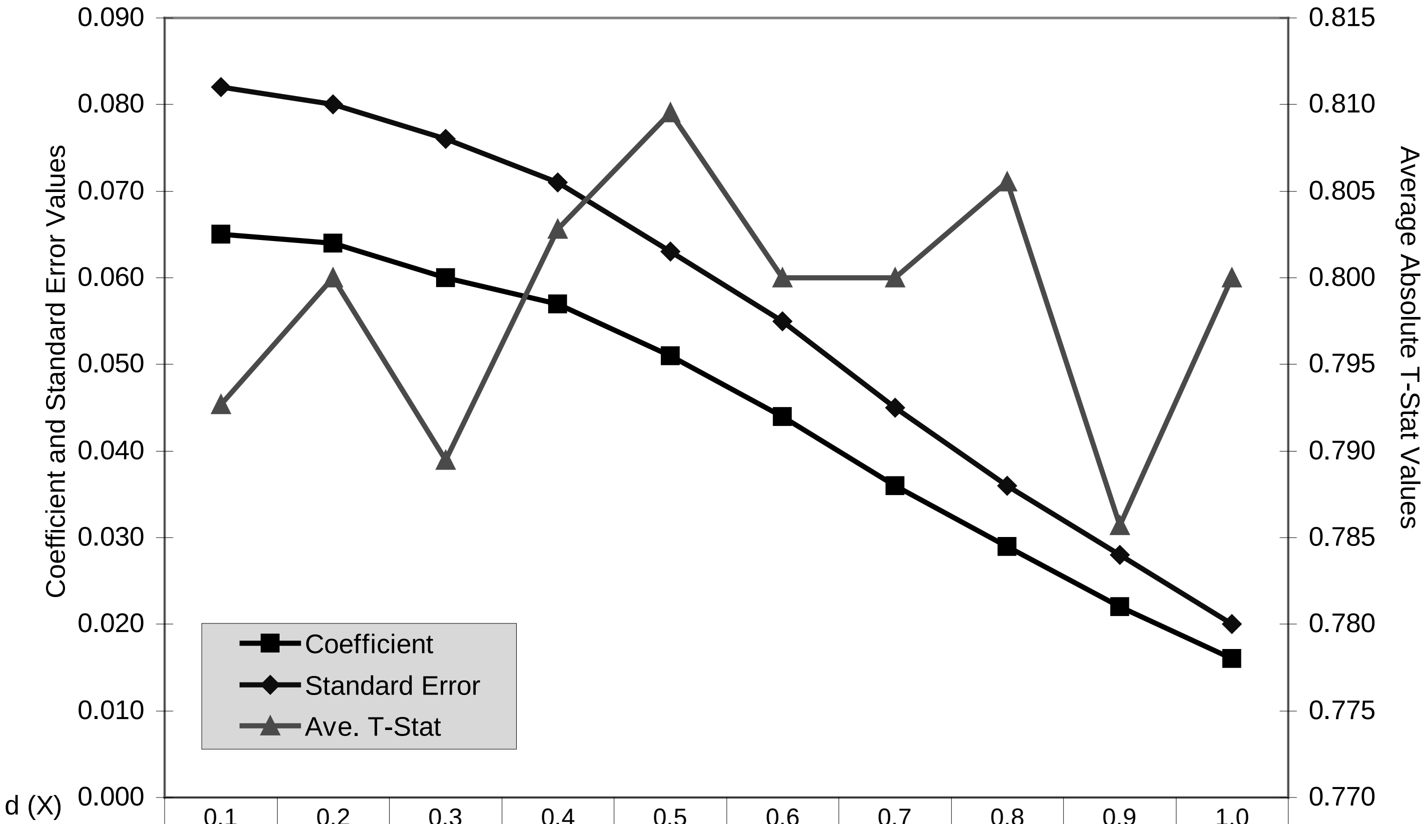


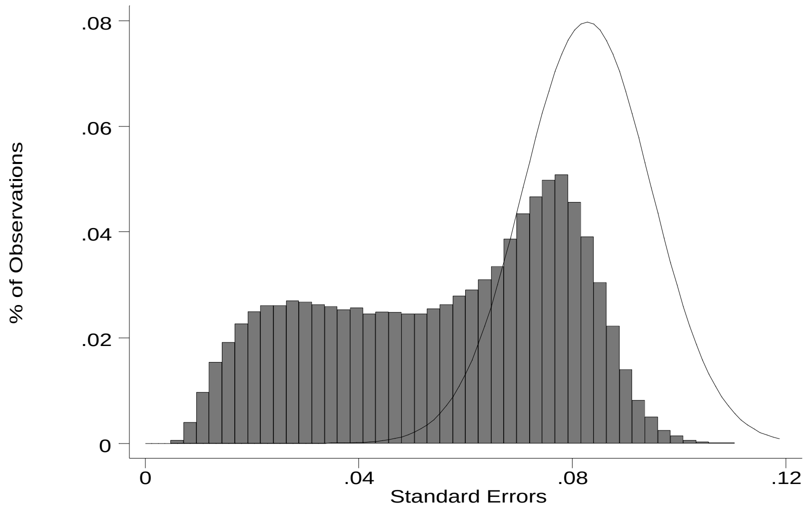
Figure 1.5: A Unit-Root Series

Figure 2.1 Simulation 2: Coefficients, Standard Errors and Average Absolute T-Stats

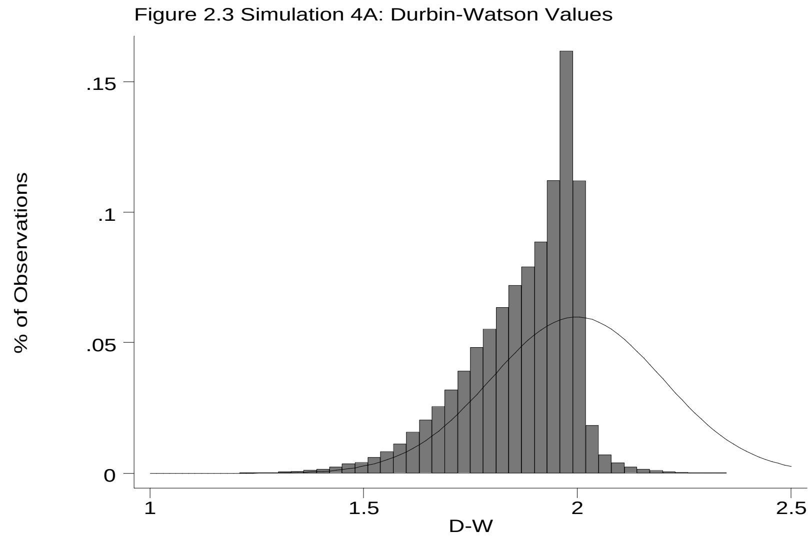


d (X)	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Coefficient	0.065	0.064	0.060	0.057	0.051	0.044	0.036	0.029	0.022	0.016
Standard Error	0.082	0.080	0.076	0.071	0.063	0.055	0.045	0.036	0.028	0.020
Ave. T-Stat	0.793	0.800	0.789	0.803	0.810	0.800	0.800	0.806	0.786	0.800

Figure 2.2 Simulation 2: Standard Errors

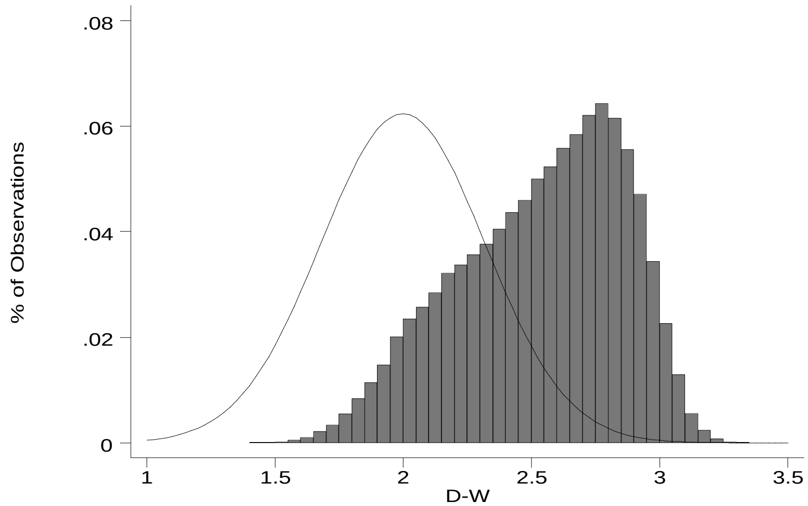


* Line indicates distribution of standard errors in Simulation 1 and control experiment.



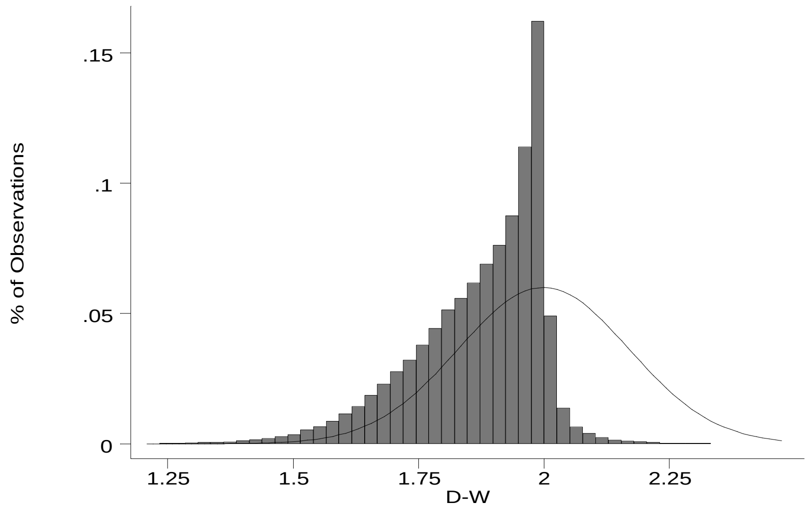
* Line indicates distribution of Durbin-Watson statistics in Simulation 1 and control experiment.

Figure 2.4 Simulation 6: Durbin-Watson Values



* Line indicates distribution of Durbin-Watson statistics
in Simulation 1 and control experiment.

Figure 2.5 Simulation 6A: Durbin-Watson Values



* Line indicates distribution of Durbin-Watson statistics in Simulation 1 and control experiment.

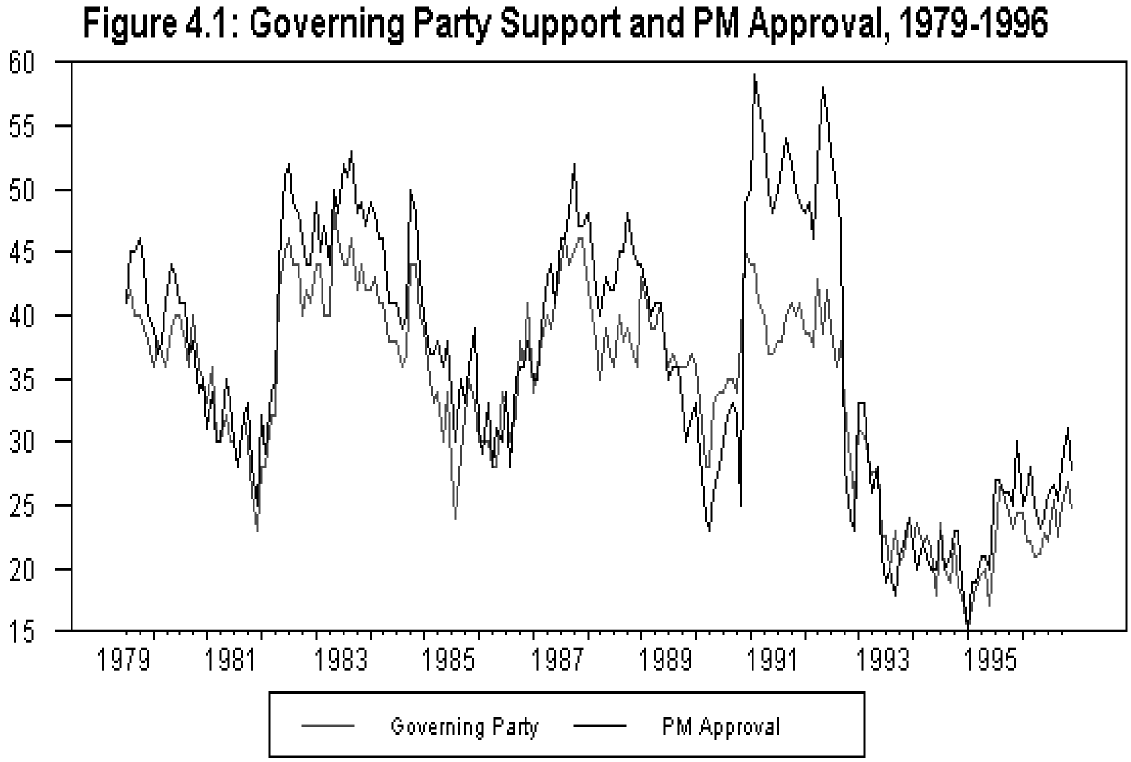


Figure 4.1: Governing Party Support and PM Approval, 1979-1996
60
55
50
45
40
35
30
25
20
15
1979
1981
1983
1985
1987
1989
1991
1993
1995
Governing Party
PM Approval

Figure 4.2: Autocorrelations of Error Correction Mechanism

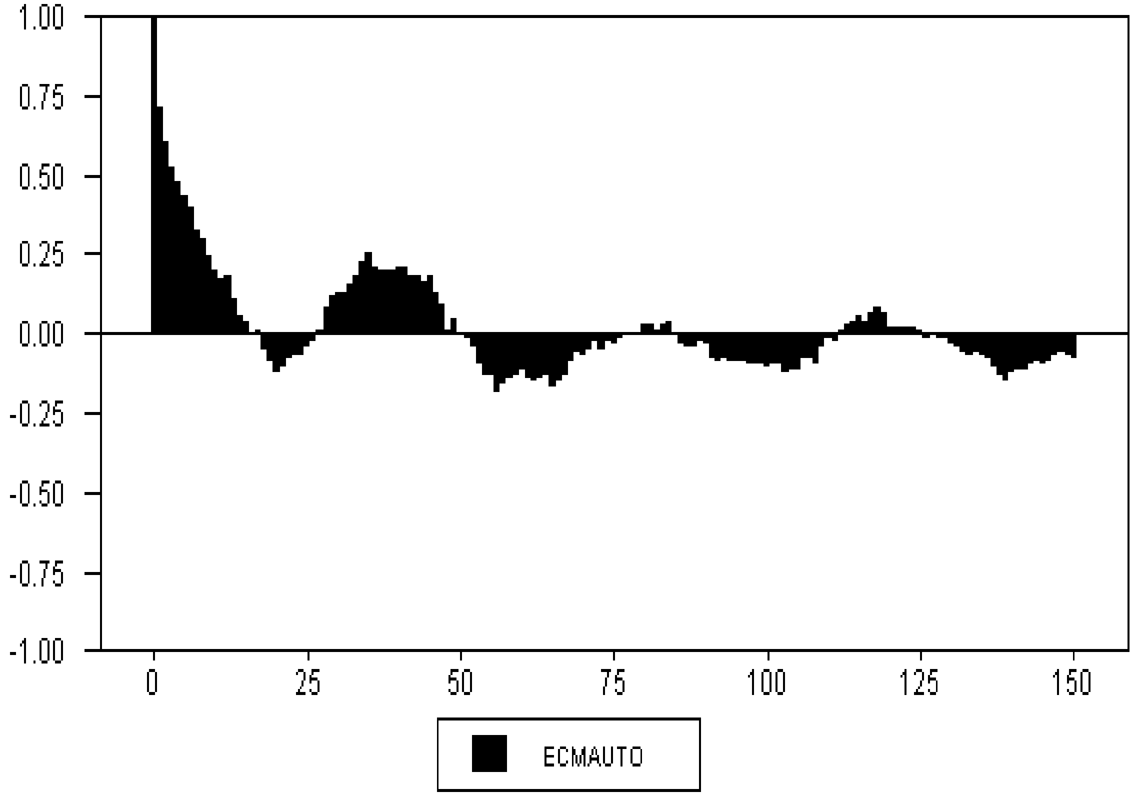


Figure 4.3: Differenced and F. Differenced Governing Party Support, 1979-1996

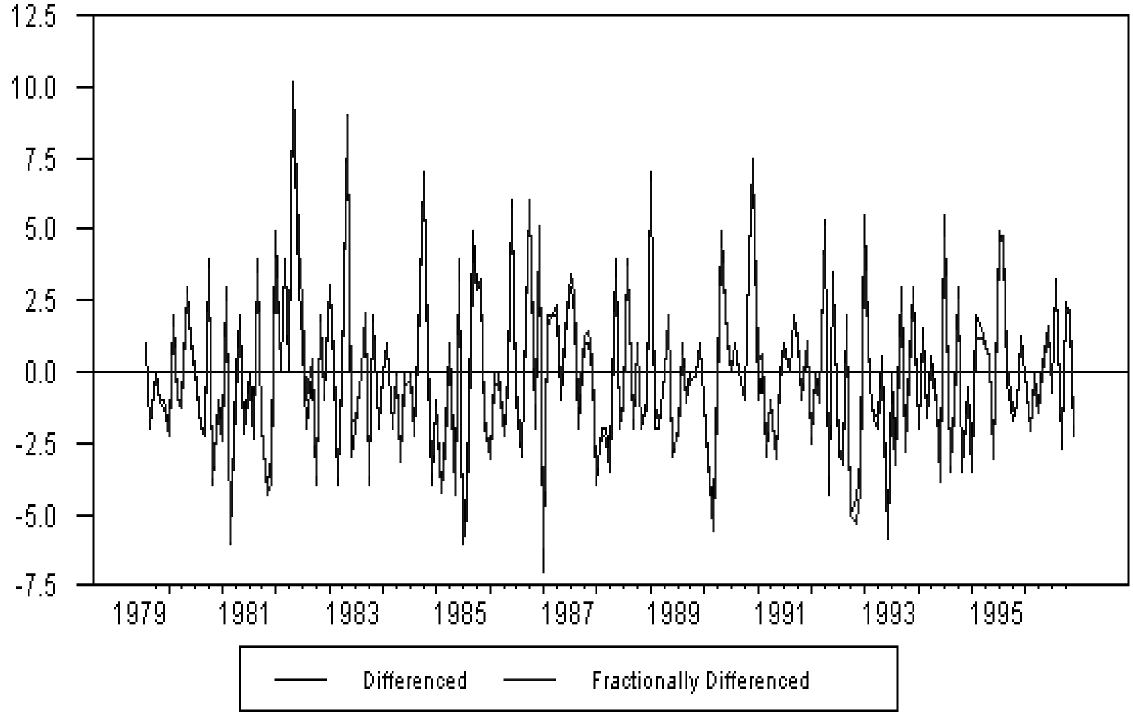


Figure 5.1: Assasination Attempt, Differenced

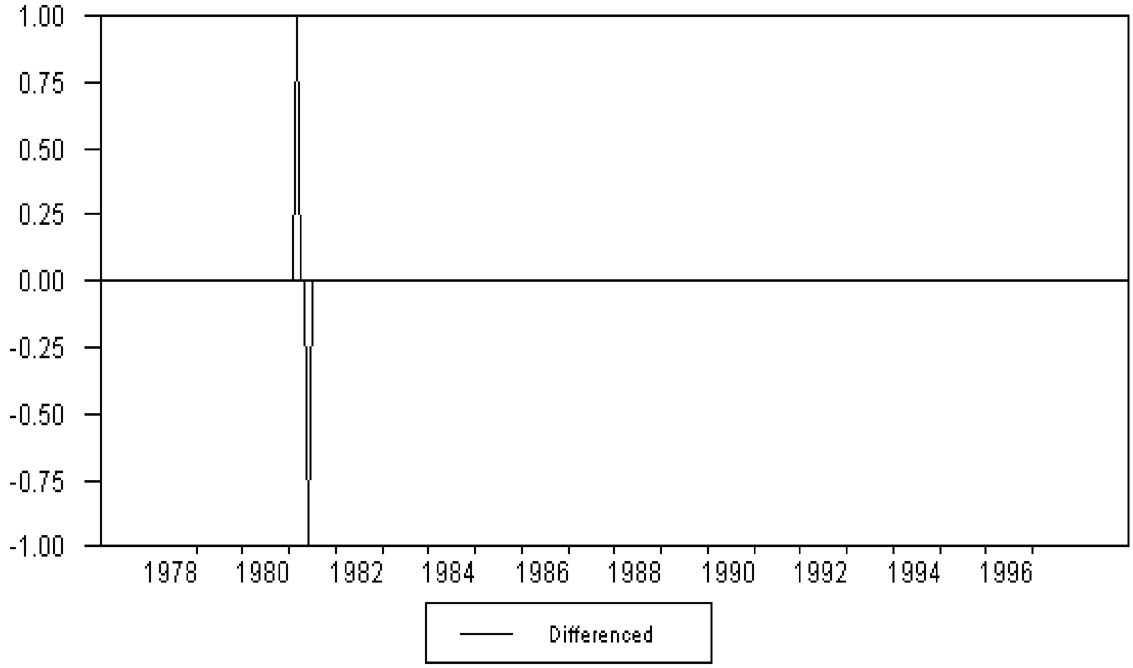
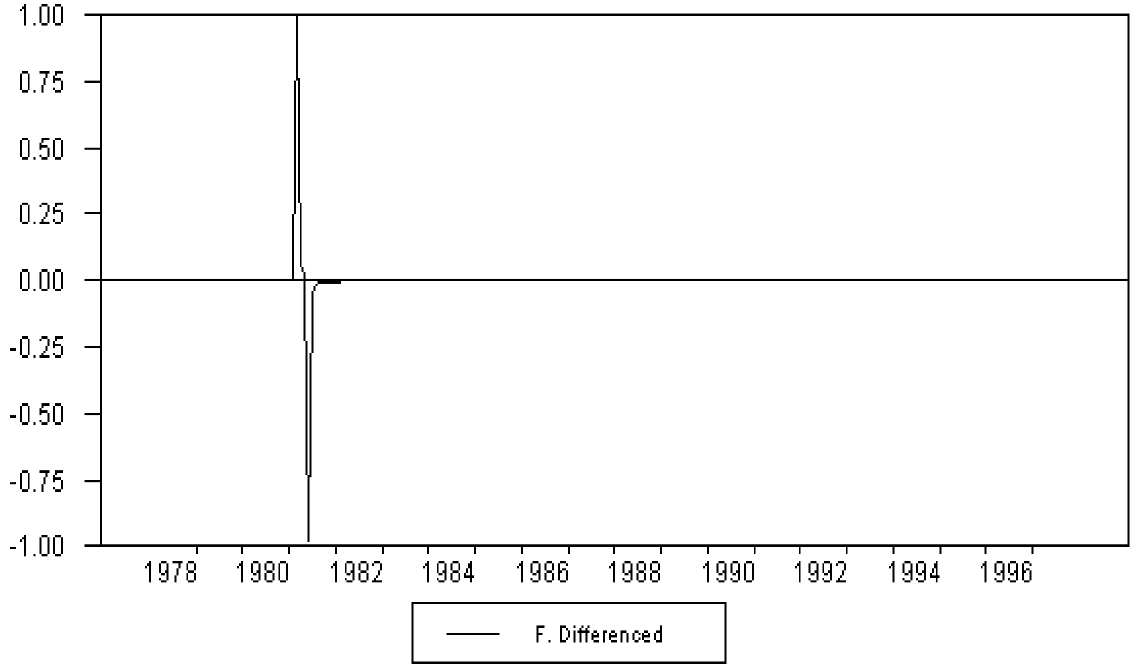


Figure 5.2: Assasination Attempt, Fractionally Differenced



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